

UNIVERSITY OF BIRMINGHAM

The effects of shocks, tobacco sales bans, and COVID-19 restrictions on mental health and wellbeing: evidence from Tanzania, South Africa, and Australia

by

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Abstract

This thesis comprises three empirical studies that delved into the impact of various shocks on mental health and wellbeing. The first study investigated the relationships between self-reported household shocks, conflict events, and food insecurity, on the one hand, and subjective wellbeing (SWB), on the other, in Tanzania. The second study examined the effect of the 2020 tobacco sales ban on the depressive feelings of South African smokers. The third chapter estimated the influence of COVID-19 lockdowns on mental health in Australia, with a specific focus on how personality traits may moderate this effect. All these studies employed individual-level panel survey data.

Using two waves of the Tanzanian National Panel Survey (TZNPS), we investigated the impact of self-reported household shocks, conflict, and food insecurity on SWB. The data was supplemented by data from the Armed Conflict Location and Event Data (ACLED) Project to match conflict events to households based on their geographical proximity. We firstly estimated the direct impact of the shocks, conflict, and food insecurity on life satisfaction using ordered Probit and linear fixed effects models. The findings suggested that only certain self-reported were negatively associated with SWB. These tended to be more idiosyncratic to the household. Additionally, we found increases in conflict events were negatively associated with SWB, albeit the magnitude of this relationship was relatively small. We further found a significant negative relationship between self-reported food insecurity and SWB. We subsequently tested for factors which moderate or mediate these relationships. We found that labour market shocks had a significantly greater impact on SWB for individuals from food insecure households, whilst receipt of financial assistance mitigated this effect. We further found the effect of food insecurity on SWB was heightened for households in the upper consumption quartile, we which postulated may reflect a greater stigma within their socioeconomic status group. Finally, our analysis largely ruled out significant mediating roles for food insecurity and consumption in the effects of the shocks and conflict on SWB.

Next, we used five waves of the South African National Income Dynamics Survey (NIDS) and three waves of the NIDS Coronavirus Rapid Response Mobile Survey (NIDS-CRAM) to estimate the impact of the tobacco sales ban introduced by the South African government in response to the COVID-19 pandemic in March 2020. Using a difference-in-differences (DD) approach, we found that the ban significantly increased frequency of depressive feelings amongst smokers who continued to smoke during the ban, but not amongst those who quit. We attributed the 'struggling quitters hypothesis' as a potential driver behind this finding. We subsequently conducted a gender-based analysis which indicated that female smokers were most susceptible to poorer mental health during the ban. We postulated this finding may reflect evidence that women are more likely to

smoke to reduce negative emotion and less likely to be successful in cessation attempts than men. Our findings therefore indicated the imposition of the ban may have had an unintended negative mental health effect on smokers and emphasise the need for appropriate cessation support to be provided to smokers.

Lastly, we exploited state-level heterogeneity in COVID-19 policies in Australia to estimate the effect of extended lockdowns on mental health, and further investigated how the 'Big Five' personality traits may moderate this effect. To this end, we utilised over 180,000 observations on individuals across 17 waves of the Household, Income, and Labour Dynamics Australia (HILDA) survey covering the period 2005 to 2021. Using an 'extended' two-way fixed effects (ETWFE) difference-in-differences design which accounted for staggered treatment timing, we firstly found that extended lockdowns significantly adversely affected the mental health of individuals in affected states, with some variations across cohorts. Moreover, extroversion, emotional stability, and openness to experience traits were found to moderate these effects to varying degrees. Highly extroverted individuals were notably more susceptible to deteriorating mental health during extended lockdowns than highly introverted individuals, although this moderating effect somewhat diminished between the 2020 and 2021 extended lockdowns. Additionally, individuals with high levels of emotional stability were largely protected from the mental health effects of extended lockdowns, as were, to a lesser extent, individuals who scored higher on openness to experience, with this latter effect dissipating in 2021. Our findings add to the growing literature documenting the unintended consequences of lockdown policies, and indicate policymakers need to seriously consider the pros and cons such polices if they were ever again required.

Declaration

I hereby declare that this thesis is my own original work except where stated otherwise by reference in the text. It has not been submitted, in whole or in part, for any other degree or qualification at this or any other university. Further, I have acknowledged and correctly referenced the work of others. No content generated by AI tools has been presented as my own work.

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Chapter One: Introduction

1. Thesis Motivation

This thesis comprises three empirical studies exploring the impact of various shocks on mental health and wellbeing. The first study investigated the relationships between self-reported household shocks, conflict events, and food insecurity, on the one hand, and subjective wellbeing, on the other, in Tanzania. The second study examined the effect of the 2020 tobacco sales ban on the depressive feelings of South African smokers. The third chapter estimated the influence of COVID-19 lockdowns on mental health in Australia, with a specific focus on how personality traits may moderate this effect. All these studies employed individual-level panel survey data.

Mental health is a global concern, with anxiety and depression ranking as the most prevalent mental disorders worldwide (WHO, 2022a). Furthermore, depressive disorders are among the leading causes of the global burden of disease, having increased significantly since 1990 (Ferrari, *et al.* 2013). Subjective wellbeing (SWB) has also gained increasing importance for governments worldwide, with many countries interested in how they can measure SWB to inform policymaking (Dolan and Metcalfe, 2012). Whilst many determinants of mental health and SWB are individual-level socioeconomic and demographic characteristics (Moeti *et al.*, 2022), exogenous shocks can also have a significant effect on individuals. These shocks can range from highly idiosyncratic events such as the loss of a household member, severe illness, or income loss to broader shocks affecting entire groups, regions, or nations.

Individuals residing in low- and middle-income countries (LMICs) may be particularly vulnerable to these shocks. LMICs often exhibit predominantly agricultural workforces, high food insecurity levels, and episodes of conflict and violence (World Bank, 2015; Smith and Birgit, 2019; Roberts and Fuhr, 2019). This holds true for Sub-Saharan African countries, which also face some of the highest poverty rates globally (Cuaresma *et al.*, 2018; Aikins and McLachlan, 2022). Individuals in LMICs may thus be more susceptible to the impact of shocks on both their economic and psychological wellbeing. Furthermore, these regions often grapple with low mental health literacy, high disease burdens, and significant treatment gaps for mental disorders (Lund *et al.*, 2010; Petersen *et al.*, 2011; Mlaki *et al.*, 2021; Ndetei *et al.*, 2023). As such, those whose mental health and wellbeing suffer from shocks may lack the resources to access necessary treatment.

The first chapter of this thesis explored the impact of various shocks on SWB in Tanzania, a Sub-Saharan African nation. Using individual-level panel data, we investigated the associations between self-reported household-level shocks, food insecurity, and conflict events, on the one hand, and life satisfaction, on the other. Although our findings offer valuable insights into how these factors

influence SWB, most shocks we considered were self-reported, whilst the exogenous measure of conflict exhibited limited variation during the study period, limiting causal inferences.

However, the emergence of the COVID-19 pandemic in 2020 provided an unprecedented exogenous global shock. Governments worldwide imposed stringent restrictions to curb the virus's spread, severely impacting on individuals' lives. These policies presented a unique opportunity to study the impact of such a drastic shock on individuals' wellbeing. A substantial body of literature has already documented the unintended economic and health consequences of COVID-19 policies (Brodeur *et al.*, 2021b; Chu *et al.*, 2020; Chiesa *et al.*, 2021). Many such studies have aimed to demonstrate the pandemic's effects on mental health, with a significant increase in the global prevalence of depression and anxiety disorders found in 2020 (WHO, 2022b).

The second and third chapters of this thesis delved into the impact of COVID-19 policies on mental health. Chapter two investigated the impact of the South African tobacco sales ban in 2020, a sudden prohibition implemented by the government in response to the COVID-19 pandemic that lasted over five months, on the mental health of smokers. Chapter three exploited state-level variation in lockdown policies in Australia to estimate the effects of extended lockdown periods on mental health, and how different personality traits may have moderated these effects.

Collectively, these three studies provided empirical evidence on the effects of different types of shocks on the mental health and wellbeing of diverse populations. They also identified individuals with characteristics rendering them more or less vulnerable to the effects of shocks within the studied countries.

The remainder of this thesis is structured as follows. Section 2 of this introductory chapter outlines each study's content and contributions to the literature. Chapter two presents the first empirical study conducted on Tanzania, chapter three outlines the second empirical study conducted on South Africa, and chapter four discusses the third empirical study conducted on Australia. Finally, chapter five concludes the thesis.

2. Thesis Outline

In chapter two, we investigated the impact of household shocks, conflict, and food insecurity on the subjective wellbeing (SWB) of Tanzanian residents. This study addressed a significant gap in the literature regarding the determinants of SWB in Sub-Saharan Africa, particularly in Tanzania, which has been underrepresented in research and characterised by studies lacking methodological rigour (Kabote, 2017; Kabote 2018; Mwanyangala *et al.*, 2010). Tanzania's predominantly agricultural workforce, high poverty rates, and susceptibility to food insecurity and conflict events make it an ideal context to examine the effects of such shocks on SWB (Adam *et al.*, 2017; World

Bank 2021a; World Bank, 2021b; Action Against Hunger, 2021). However, empirical evidence on how these events affect SWB is limited. Additionally, previous research has suggested self-reported household shocks and conflict can have broader economic implications, affecting consumption, poverty rates, and food insecurity, which, in turn, have often been found to be associated with SWB and mental health outcomes (Dercon & Krishnan, 2000; Porter, 2012; Alloush, 2018; d'Errico *et al.*, 2018; Frongillo *et al.*, 2017; Elgar *et al.*, 2021; Na *et al.*, 2018; Asfahani *et al.*, 2019; Trudell *et al.*, 2021). This suggests self-reported shocks and conflict may also be indirectly related to SWB through their effect on these factors.

We explored these potentially intertwined relationships utilising two waves of individual-level panel data from the Tanzanian National Panel Survey (TZNPS) supplemented with conflict data from the Armed Conflict Location and Event Data (ACLED) Project. We firstly estimated the direct relationships between self-reported household shocks, conflict, and food insecurity on the one hand, and life satisfaction on the other. We found certain self-reported household shocks, such as illness of a household member or death of a family member, were negatively associated with SWB. These tended to be more idiosyncratic to the household and more likely to have consequences which permeated to all household members. Additionally, we found increases in conflict events were negatively associated with SWB, albeit the magnitude of this relationship was relatively small. We further found a significant negative relationship between self-reported food insecurity and SWB, whilst also providing novel evidence that a households' risk of food insecurity was also negatively associated with SWB.

We subsequently tested for potential moderating effects in these relationships. Specifically, we examined whether experience of food insecurity increased the impact of self-reported shocks and conflict on SWB, before further exploring whether households in the upper consumption quartile or who received of financial assistance from the government or a non-governmental organisation (NGO) were protected from the effects shocks and conflict on SWB. We found the negative association between labour market shocks and SWB was significantly larger amongst food insecure households, as was the association between conflict intensity and life satisfaction. Conversely, households in the upper consumption quartile were not found to be protected against the impacts of the significant self-reported shocks and conflict, however receipt of financial assistance mitigated the SWB effects of labour market shocks. Lastly, we tested if cross-national findings from the literature that food insecurity exhibits a stronger negative relationship in countries with a lower prevalence of food insecurity (Frongillo *et al.*, 2017; Elgar *et al.*, 2021) applied to a within-country setting. Given food insecurity rates were relatively lower amongst households from the upper consumption quartile, we interacted this with self-reported food insecurity and found

evidence for applicability of these cross-national findings to a within-country setting. We speculated this may reflect increased stigma around food insecurity for individuals in this socioeconomic class.

Finally, given the evidence that self-reported shocks and conflict affect food insecurity and consumption rates (Dercon & Krishnan, 2000; Porter, 2012; Alloush, 2018; d'Errico *et al.*, 2018; Frongillo *et al.*, 2017; Elgar *et al.*, 2021; Na *et al.*, 2018; Asfahani *et al.*, 2019; Trudell *et al.*, 2021), we tested whether food insecurity and consumption were significant moderating variables in the effect of shocks on conflict on SWB. However, we found little evidence for this, suggesting shocks and conflict predominantly exhibited a direct influence on life satisfaction in our sample.

While chapter two provided valuable insights into the impact of different shocks on SWB, it was constrained by reliance on self-reported shocks and limited variation in exogenous conflict shocks. Therefore, chapters three and four adopted a different approach, leveraging large-scale exogenous shocks generated by COVID-19 policies.

In chapter three, we investigated the mental health impact of the tobacco sales ban imposed by the South African government at the beginning of the pandemic, a dimension often overlooked in previous research primarily focused on market and behavioural effects of the ban (van Walbeek *et al.*, 2020; van Walbeek *et al.*, 2021; van der Zee *et al.*, 2023). The study used individual-level panel data from the South African National Income Dynamics Survey (NIDS) conducted from 2008 to 2017 and the NIDS Coronavirus Rapid Response Mobile Survey (NIDS-CRAM) from 2020 and 2021. The exogenous nature of the policy allowed us to implement difference-in-differences (DD) estimation and employ entropy balancing to enhance causal inference. We found a positive but statistically insignificant effect of the ban on the frequency of depressive feelings among smokers.

We subsequently tested for a heterogeneous effects of the ban using triple difference-in-differences specifications (DDD). We found significantly increased frequencies of depressive feelings amongst smokers who continued to smoke during the ban, but not amongst those who quit. Given most smokers indicated they attempted to quit but were ultimately unsuccessful (van Walbeek *et al.*, 2020; van der Zee *et al.*, 2023; van Walbeek *et al.*, 2023), we proposed a key mechanism behind this finding was the so-called 'struggling quitters hypothesis', which has surfaced from empirical evidence that failed cessation attempts can negatively impact mental health (Berlin, 2010; Capron *et al.*, 2014). Second, we conducted a gender-based analysis which indicated female smokers were most susceptible to poorer mental health during the ban. We postulated this finding may reflect evidence that women are more likely to smoke to reduce negative emotions (Livson and Leino, 1988; Zuckerman *et al.*, 1990 Brandon and Baker, 1991;

Berlin *et al.*, 2003; Fidler and West, 2009; Pang *et al.*, 2014) and less likely to be successful in cessation attempts than men (Ward *et al.*, 1997; Smith *et al.*, 2016).

These findings contribute to the literature on the tobacco sales ban by highlighting its unintended negative consequences on the mental health of smokers, underscoring that not only did it fail in its objectives and lead to the entrenching of the illicit tobacco market, but that it was also a public health policy mistake. We proposed policymakers should instead consider the market-based solutions such as increased excise duties to reduce smoking rates advocated by authors such as van Walbeek *et al.* (2020), van der Zee *et al.* (2023), and van Walbeek *et al.* (2023). This would likely achieve similar rates of cessation (van Walbeek *et al.*, 2021) without significantly impacting mental health, providing governments ensure accessible and affordable smoking cessation support to those attempting to quit, of which there was a complete absence during the ban.

Chapter four explored the impact of extended COVID-19 lockdown policies on mental health in Australia, focusing on the moderating role of the "Big Five" personality traits. In response to the pandemic, governments worldwide implemented stringent policies including stay-at-home orders to contain the virus, which proved effective in reducing hospitalisations and mortality, but raised concerns about unintended consequences on various aspects of citizens' lives, including mental health (Bradbury-Jones and Isham, 2020; Santomauro *et al.*, 2021; Woc-Colburn and Godinez, 2022).

Numerous studies conducted on Europe and the United States (US) have established associations between COVID-19 policy stringency and deteriorating mental health outcomes. However, these studies often faced methodological limitations, such as relying on cross-sectional data or failing to account for pre-pandemic trends (Garcia-Prado *et al.*, 2022; Adams-Prassl *et al.*, 2022; Toffolutti *et al.*, 2022; Aknin *et al.*, 2022; Brodeur *et al.*, 2021; Arendt *et al.*, 2020; Ramiz *et al.*, 2021; Serrano-Alarcon *et al.*, 2022; Schmidtke *et al.*, 2021). Even studies using robust panel data frequently relied on weak indicators of mental health such as Google trends data or crisis hotline calls, or employed weak identification strategies as they lacked contemporaneous treatment and control groups (Arendt *et al.*, 2020; Brodeur *et al.*, 2021; Ramiz *et al.*, 2021; Schmidtke *et al.*, 2021; Serrano-Alarcon *et al.*, 2022).

A growing body of literature has investigated how various groups were affected differently by COVID-19 policies, often examining differences between genders and age groups (Ramiz *et al.*, 2021; Adams-Prassl *et al.*, 2022; Garcia-Prado *et al.*, 2022; Hale *et al.*, 2023a). Additionally, emerging research has explored how different personality traits may either exacerbate or mitigate the mental health effects of these policies. However, similar to broader studies on lockdowns and mental

health, many of these investigations have been methodologically limited, relying on cross-sectional samples to simply estimate associations between traits and mental health outcomes during the pandemic (Wei, 2020; Nikcevic *et al.*, 2021; Pauly *et al.*, 2021; Shokkron and Nicoladis, 2021; Zhang *et al.*, 2021; Margetic *et al.*, 2022; Michinov and Michinov, 2023). Further, those using panel data have fallen short of identifying causal moderating effects due to the absence of well-defined treatment and control groups (Zacher and Rudolph, 2021; Proto and Zhang, 2021; Staneva *et al.*, 2022).

The COVID-19 policy landscape in Australia offered a unique opportunity to estimate the impact of lockdown policies on mental health and investigate how the Big Five personality traits might moderate this relationship. Australia's federal government system granted significant policy-making authority to state governments. Consequently, while all states initially followed national lockdown directives in the first two months of the pandemic, substantial policy divergence emerged during the latter half of 2020 and throughout 2021 (Edwards *et al.*, 2022). This situation presented an ideal quasi-natural experiment, allowing for more robust causal estimates than many existing studies in this field.

The study employed 17 waves of the Household, Income, and Labour Dynamics Australia (HILDA) survey, totalling over 180,000 observations from 2005 to 2021. Using an 'Extended' Two-Way Fixed Effects (ETWFE) methodology to account for policy heterogeneity across states (Wooldridge, 2021), the research provided causal estimates of the effect of lockdown on mental health and for moderating effects of the Big Five personality traits. The findings indicated extended lockdowns significantly adversely affected the mental health of individuals in affected states, with some variations across cohorts. Moreover, extroversion, emotional stability, and openness to experience traits were found to moderate these effects to varying degrees, suggesting highly extroverted individuals were most affected, while the most emotionally stable appeared to be protected. Converse to expectations, openness provided a protective effect, although this was only found in the 2020 extended lockdown. This suggests more open individuals may have appraised extended lockdown as a novel opportunity for personal growth and to explore their innate creativity. These findings provide a novel contribution to the literature in this context, whilst also improving methodologically on previous studies into the moderating role of personality traits during the pandemic. This research emphasises the importance of considering the mental health implications when implementing lockdown policies during pandemics.

Overall, these chapters provide valuable insights into the multifaceted relationships between various shocks, mental health, and wellbeing across different contexts and populations, contributing to a deeper understanding of these critical issues.

Chapter Two: Household Shocks, Food Insecurity, Conflict, and Subjective Wellbeing: An Analysis of the Tanzanian National Panel Survey

1. Introduction

In Sub-Saharan Africa, research on the determinants of mental health and subjective wellbeing (SWB) is notably lacking (Kabote, 2017). In Tanzania specifically, studies exploring socioeconomic factors influencing SWB have been sparse and often marred by small, non-representative cross-sectional samples, resulting in methodological limitations (Mwanyangala *et al.*, 2010; Kabote, 2018). Moreover, comprehensive investigations into the impact of various self-reported household shocks on SWB in Sub-Saharan Africa have been limited. Many studies have merely considered these shocks as part of broader analyses, utilising simple measures amalgamating multiple shocks into a single metric or, in some cases, failing to specify the nature of the shocks altogether (Jiao *et al.*, 2015; Jansen *et al.*, 2015). More extensive research has explored the connection between self-reported household shocks and observable covariate shocks with other welfare outcomes, with many studies finding links between these events and higher rates of poverty and food insecurity, and lower levels of consumption (Dercon and Krishnan, 2000; Porter, 2012; d'Errico *et al.*, 2018).

These findings motivated further inquiry into the existing literature on the relationship between food insecurity and SWB. Cumulatively, studies predominantly relying on the multinational Gallup World Poll Survey have revealed food insecurity significantly predicts lower life evaluation and reduced positive affect (Frongillo *et al.*, 2017; Elgar *et al.*, 2021; Na *et al.*, 2018; Asfahani *et al.*, 2019). A notable finding from these studies is this relationship was more pronounced in countries with lower levels of food insecurity, implying a potentially weaker link between food insecurity and SWB in nations like Tanzania. However, the multinational nature of these studies hindered detailed investigations into within-country variations and subgroup analyses.

In addition, there has been a relative dearth of research exploring the impact of conflict events on SWB, with no studies identified examining this relationship in Sub-Saharan Africa. Nevertheless, some studies have discovered evidence suggesting conflict events can affect other welfare outcomes in this context, such as food insecurity and individuals' expectations about their future welfare (Dabalen and Paul, 2014; Bozzoli *et al.*, 2021).

Collectively, the existing literature indicates a potential interplay between shocks, food insecurity, conflict, and SWB. Consequently, this study embarked on an empirical exploration of these relationships. To this end, we utilised two waves of individual-level panel data from the Tanzanian National Panel Survey (TZNPS), conducted in 2010/11 and 2012/13. This dataset was augmented

with an objective measure of conflict events, obtained from the Armed Conflict Location and Event Data (ACLED) Project, and aligned with the households surveyed in the TZNPS based on geographical location. We initiated our investigation by estimating the influence of numerous self-reported household shocks, two metrics reflecting food insecurity incidence and risk, and variations in conflict intensity on life satisfaction.

Our estimation methods encompassed two approaches. Initially, we employed the ordered Probit estimator with Mundlak-style corrections to partially control for unobserved time-invariant heterogeneity. Subsequently, we conducted a robustness check using linear fixed effects estimation. Our study also explored potential moderating and mediating factors in these relationships. We first examined whether individuals reporting food insecurity were more susceptible to the impacts of shocks and conflict on their SWB. We subsequently assessed protective mechanisms through higher household consumption levels (indicating greater economic resources) and assistance from government or non-governmental organisations (NGOs). Finally, our study probed the potential mediating roles of food insecurity and consumption in the relationships between shocks, conflict, and SWB.

Our results revealed only specific self-reported shocks significantly correlated with diminished SWB. Typically, these shocks were more idiosyncratic to households, but were also more likely to permeate to all household members. Limited evidence supported the proposition that food insecurity and consumption mediated these relationships, suggesting that, when observed, these shocks generally exerted a direct impact on SWB. Some evidence was found for moderating effects, most notably where households reporting food insecurity were more vulnerable to reduced SWB following labour market shocks. Moreover, receipt of government or NGO assistance acted as a protective factor against these impacts. These findings emphasised the importance of robust social safety nets in preserving individuals' wellbeing when exposed to labour market shocks.

The study also demonstrated a negative association between food insecurity and SWB, which was more pronounced among those in the highest consumption quartile. This suggests the relatively lower prevalence of food insecurity in this social group might amplify its effect on SWB, aligning with findings from multinational studies (Frongillo *et al.*, 2017; Elgar *et al.*, 2021). We contributed novel evidence revealing a negative relationship between increased conflict and SWB in Tanzania. Despite the limited impact observed due to low conflict levels during the study period, this finding holds significant importance given the growing threat of conflict in Tanzania (Blocher and Kileli, 2020; Bergius *et al.*, 2020; Mangena and Pherudi, 2019; AP News, 2020; Walwa, 2022). Lastly, we included numerous socioeconomic variables in our models, allowing us to address a dearth in

methodologically rigorous studies into the determinants of SWB in Tanzania, providing evidence for which factors are important contributors to the wellbeing of the Tanzanian population above and beyond shocks, conflict, and food insecurity.

The subsequent sections of this chapter are structured as follows. Section 2 provides an overview of Tanzania and its significance as a case study. Section 3 conducts a literature review. Section 4 outlines the hypotheses tested. Section 5 provides information TZNPS and ACLED data, along with presenting descriptive statistics for our baseline sample. Section 6 elucidates our baseline specification and estimation strategies used to assess our hypotheses. Section 7 presents and discusses the outcomes of our econometric models. Lastly, Section 8 concludes by summarising key findings, addressing strengths and limitations, and proposing policy implications and future research directions.

2. Background

The following section provides background information on Tanzania, and why it provides a compelling case to study the relationship between household shocks, food insecurity, conflict, and subjective wellbeing (SWB).

Located in East Africa, Tanzania was designated by the World Bank as a low-income country until 2020 when it moved to being a lower-middle income country following two decades of sustained economic growth (World Bank, 2021a). Although falling, in 2019 approximately 65% of employment remained in the agricultural sector (World Bank, 2021b), whilst the agricultural sector still contributed to approximately 27% of GDP (World Bank, 2021c). According to the World Food Programme (2021), Tanzania currently produces enough food to feed its population, however the poor and other marginalised communities often have limited access to it. Indeed, much of the population is at risk of food insecurity, with pressures coming from several sources including agricultural production shocks and food price inflation. For example, in 2019 food insecurity in Tanzania increased following a period of prolonged dry weather, armyworm infestations, and erratic rainfall, leading to an estimated 25% of districts having vulnerable food insecurity pockets, up from just 5% in 2018 (Action Against Hunger, 2021). Furthermore, Tanzania was affected by the world food price crisis of 2010-2012, during which food price inflation rose rapidly from approximately 5% at the start of 2010 to almost 26% at the peak of the crisis in December 2011 (Adam *et al.*, 2017)

Pressures on food security also come at a household- and individual-level. According to the World Bank (2021a), in 2019 approximately 26.1% of the population lived below the national poverty line of TSh 49,320 ($1.35 PPP per person per day) whilst almost 50% of the population lived below the international poverty line of $1.90 PPP per person per day. Thus, a significant proportion of the population are already extremely poor, leaving them vulnerable to food insecurity in the face of household-level or individual-level shocks to income. Furthermore, many others live close to the poverty line, with such shocks potentially tipping them into poverty and having further knock-on effects on their welfare.

Although Tanzania is relatively peaceful compared to many African countries, some experts postulate that climate change may increase levels of internal conflict in Tanzania due to increased resource scarcity, especially water and food (Blocher and Kileli, 2020). This may ultimately lead to migration from rural to urban areas, which under these circumstances can fuel pre-existing divides between communities and create new competition over natural resources, leading to localised flare-ups over migration- or land-related demographic shifts. In turn, this can escalate and contribute

to civil unrest and undermine state authority (Blocher and Kileli, 2020). Furthermore, the threat of external conflict is also increasing in Tanzania. Most notably, in neighbouring Mozambique, Islamic insurgents have been fighting in the Cabo Delgado province which borders Tanzania to the south, and have even brought violence into Tanzania with an attack which killed at least 20 civilians in the Mtwara region in October 2020 (AP News, 2020). In response, Tanzania forces have agreed to cooperate in a joint effort with Mozambique against the insurgents (Aljazeera, 2020). This threat of external conflict may ultimately lead to even greater pressure on resources, for example due to refugees fleeing violence, although currently the Tanzanian government are reportedly forcibly deporting those crossing the border from Mozambique (UNHCR, 2021).

Overall, despite improvements over the past decades, a large proportion of the Tanzanian population still live close to or below the poverty line. As such, they are vulnerable to severe food insecurity, and various events could tip those already close to the edge into a situation where they do not have enough food to feed their family, and further worsen the welfare of those who are already struggling. Such events could be aggregate level shocks, such as food price inflation, agricultural or environmental shocks to productivity, or conflict events, or household level shocks which have financial implications such as job loss or the death of a household member. In turn these events may have an indirect impact on the wellbeing of individuals, as well as a direct impact due to the unpleasant nature of them. It is therefore important to understand to what extent such events may impact the wellbeing of the population, especially considering the increasing threat of climate change and conflict, and the implications these have on food security. This research is even more pertinent given the fact that despite Sub-Saharan Africa being bottom of the wellbeing rankings (Gallup-Healthways, 2014), there is a dearth of empirical research into SWB in the region (Kabote, 2017).

3. Literature Review

This section presents a selective review of the literature. Section 3.1 presents studies which have examined how subjective wellbeing (SWB) has been conceptualised in the economic literature and reviews the validity of the measures often utilised. Section 3.2 provides details on studies which have examined the socioeconomic and demographic determinants of subjective wellbeing (SWB) in low- and middle-income countries (LMICs). It begins with studies conducted using data from Sub-Saharan Africa. Due to a lack of robust empirical studies, this is subsequently supplemented with evidence from other LMICs. Section 3.3 provides an overview on the literature on the relationship between shocks and various welfare measures, beginning with SWB, then mental health, and finally economic welfare outcomes. Section 3.4 then presents the literature on the relationship between food insecurity and SWB, again drawing on studies conducted both in Sub-Saharan Africa and other LMICs. Section 3.5 explores the literature on how conflict affects SWB and other welfare outcome measures. Finally, Section 3.6 briefly summarises the key findings from the literature and highlights the contribution of this paper. A summary of the findings from the empirical studies is presented in Tables A1-A6 in Appendix 1A.

3.1 Conceptualising, Measuring, and Estimating Subjective Wellbeing in Economic Research

The following sub-section begins by exploring the literature on how SWB has been conceptualised and measured for use in economic and other social science research. Subsequently, methodological concerns pertaining to the econometric estimation of SWB equations are examined.

3.1.1 Conceptualising and Measuring Subjective Wellbeing

Traditionally in economics, individual wellbeing has been measured using 'decision utility', inferring ordinal preferences from the decisions made by rational agents (Akay *et al.*, 2017). However, it can be argued that decision utility fails to capture the utility associated with different experiences. Consequently, literature across psychology and social science has emphasised alternative measures, such as SWB (Akay *et al.*, 2017). SWB can trace its theoretical origins to the work of Bentham, who proposed wellbeing is rooted in pleasure and pain (Dolan *et al.*, 2011). SWB is typically measured across three broad categories: evaluation, experience, and eudemonic (Dolan *et al.*, 2011).

Evaluative measures of SWB are the most prevalent in social science research, often involving individuals assessing their overall life satisfaction or satisfaction within specific life domains, such as health or employment (Dolan *et al.*, 2011). These assessments are usually collected using Likert-

type scales, where individuals indicate their satisfaction levels, ranging from 'very dissatisfied' to 'very satisfied', and are frequently employed in global household surveys (Diener *et al.*, 2013).

A similar approach involves measuring general happiness, as seen in Cantril's (1965) Self-Anchoring Scale. Respondents rate their life on an 11-step ladder, with 0 representing the 'worst possible life' and 10 representing the 'best possible life'. This measure is utilised in surveys such as the Gallup World Poll (Deaton, 2011). These scales exhibit strong reliability and validity, having been shown to converge with non-self-report measures, reflect known group and societal differences, and be responsive to changing conditions (Diener *et al.*, 2013).

Evaluative measures can also encompass general affect, where scales gauge individuals' responses to statements about positive and negative emotions like excitement, worry, and anxiety (Diener *et al.*, 2013). Examples include Watson *et al.*'s (1988) Positive and Negative Affect Scale and the General Health Questionnaire (GHQ). Some authors distinguish between these evaluative measures, categorising life satisfaction scales as capturing cognitive SWB and measures like the GHQ as capturing affective SWB (Tsurumi *et al.*, 2020).

These different types of evaluative measures of wellbeing may demonstrate different properties. For example, Powdthavee and van den Berg (2011) utilised individual-level panel data from the British Household Panel Survey (BHPS) to compare the relationships between four health and wellbeing measures and 'health shocks', long-term health conditions, and income. The two wellbeing measures examined were life satisfaction and the 12-item General Health Questionnaire (GHQ-12). The authors outlined that that life satisfaction aims to elicit an individual's past, present, and future global wellbeing, and has been demonstrated to be a measure of cognitive wellbeing as opposed to emotional affect. The GHQ-12 on the other hand is a measure of mental wellbeing, and can be considered as a good proxy for mental stress and strain. The findings illustrated significant heterogeneity in the magnitude of the relationships between the health shocks, long-term health conditions, and income with the two wellbeing measures. The authors then calculated these relationships in monetary terms, and illustrated that measures of overall wellbeing, such as life satisfaction, generate significantly smaller values of health compensation for the same condition compared to measures of affective wellbeing, domain-specific wellbeing, and self-reported health. The implications of Powdthavee and van den Berg's (2011) study is that measures such as the GHQ-12 are likely to be more sensitive to short-term fluctuations compared to global wellbeing measures such as life satisfaction. Indeed, by construction, measures like life satisfaction should reflect the enduring, overall quality of people's lives, and therefore should not be strongly influenced by their immediate contextual circumstances (Hudson et al., 2017).

A further consideration when eliciting SWB through surveys is the possibility of self-report bias. This reflects deviations between the self-reported and true values of the same measures (Bauhoff, 2014). Such bias may be introduced in survey data whereby social desirability, cognitive processes, and survey conditions can alter individual's responses (Bound et al., 2001). Evidence on the extent to which factors such as social desirability bias responses to measures of SWB is mixed. For example, Reisinger (2022) found that social desirability may substantially bias measures of SWB utilised in three US-based longitudinal surveys. Kozma and Stones (1987) also found evidence that social desirability may contribute to individuals generally overrating their SWB, however they noted that this tendency tends to be consistent across different sub-groups, and therefore is not a major threat to the validity of measures of SWB. Alternatively, Caputo (2017) showed that social desirability accounted for only a very small amount of variance in SWB measures, a finding echoed by Sepulveda et al. (2020). However, both studies only utilised small web-based sample of individuals. Overall, although not perfect, self-reported measures of SWB tend to exhibit good psychometric properties and remain useful for research purpose (Lucas, 2018).

3.1.2 Estimating Subjective Wellbeing

Studies on the determinants of SBW typically adopt the following form:

$$SWB_{report} = r(h)$$

Here, self-reported SWB, such as overall life satisfaction, is a reporting function *(r)* of true SWB *(h)*. True SWB itself is a function of socioeconomic and environmental factors (*X),* and is often empirically modelled as an additive function:

$$SWB_{it} = \alpha + \beta X_{it} + \varepsilon_{it}$$

whereby individual differences are captured in the error term (ε_{it}) (Dolan *et al.*, 2008).

The estimation of the SWB equation relies on assumptions about the dependent variable. In the case of life satisfaction scales, SWB can be assumed to be either cardinal or ordinal. Cardinality implies the difference in SWB between a life satisfaction score of 4 and 5 for one individual is identical to the difference between 8 and 9 for another individual (Ferrer-i-Carbonell and Frijters, 2004). This assumption allows for the use of linear regression methods by treating the dependent variable as continuous.

Ordinality treats SWB as a latent variable and assumes the relative difference between each response is unknown, but all individuals share the same interpretation of each answer (Ferrer-i-Carbonell and Frijters, 2004). When assuming ordinality, non-linear estimation methods like ordered Probit or ordered Logit estimators must be used. Ferrer-i-Carbonell and Frijters (2004)

empirically demonstrated that assuming ordinality or cardinality has little impact on the results regarding the determinants of life satisfaction. However, controlling for individual-level fixed effects can significantly alter estimated coefficients.

This poses a challenge when using traditional ordered Probit or Logit models, as fixed effects are precluded due to the incidental parameters problem (Greene, 2004). Solutions have been proposed, including Baetschmann *et al.*'s (2015) 'Blow up and cluster' estimator. However, this method does not allow for straightforward calculation of partial effects post-estimation, limiting analysis to examining the direction and significance of estimated coefficients. An approach offering a balance is Wooldridge's (2019) correlated random effects estimator with Mundlak-style corrections. This method augments the model with the individual-level means of each time-varying regressor, providing partial control of unobserved heterogeneity. It also allows for the calculation of partial effects for each regressor post-estimation. Alternatively, Riedl and Geishecker (2014) recommend reverting to a linear fixed effects model, returning to the assumption of cardinality of the dependent variable.

3.2 Socioeconomic Determinants of Subjective Wellbeing in Low- and Middle-Income Countries

3.2.1 Studies on Sub-Saharan Africa

In this sub-section, we explore studies investigating the determinants of SWB in Sub-Saharan Africa. These studies were essential for identifying key variables for our SWB analysis and methodological limitations within the existing research. Since some of the studies included the same variables using the same data, particularly those using the South African National Income Dynamics Study (NIDS), not all the results are reported here for the sake of brevity. However, this information is provided by Table A1 in the Appendix 1A.

Kabote (2018) undertook an exploration into the wellbeing of female entrepreneurs in Tanzania's Arumeru district. The study examined a small sample of 180 individuals drawn from six villages across the district. The study found entrepreneurship was positively associated with wellbeing. Conversely, being married was found to be negatively associated with wellbeing, while age exhibited a significant positive relationship with wellbeing. However, the study's findings were limited by its small sample size and its focus on a specific demographic group within Tanzania.

Mwanyangala *et al.* (2010) explored the determinants of wellbeing and health status among older individuals in Tanzania's rural Ifakara area. The data for this study were collected in 2007, targeting all households with members aged 50 and above in the region. The sample included 2,463 men and 2,668 women. The study's findings highlighted that being a woman, single, and belonging to

the lower socioeconomic quartiles were associated with greater odds of reporting below-median quality of life and health status. However, similar to Kabote (2018), this study was constrained by its specific sample, cross-sectional data, and the limited number of determinants considered.

Moving away from Tanzania, Nanor *et al.* (2021) conducted research on SWB determinants in rural Ghana. Their sample comprised 320 households, with data collected in 2019. SWB was evaluated using a happiness with life scale, and socioeconomic factors were among those considered. The authors employed bivariate correlation analysis to identify factors to include in their final ordered Probit model. Their results indicated age, healthcare facility use, water source, occupation, and religion influenced SWB. The authors noted that although income was not found to significantly determine SWB, many of the factors found to be significant determinants were related to income, therefore they postulate the importance of income to SWB cannot be dismissed. Nevertheless, while valuable given it is one of the few studies which investigate determinants of SWB in an African nation, this study's limitations include its relatively small sample size and its focus on a specific community in rural Ghana.

The remaining papers reviewed utilised data from South Africa. Blaauw and Pretorius (2013) conducted an exploratory analysis of SWB determinants using the first wave of the South African National Income Dynamics Survey (NIDS) data from 2008. The study included a sample size of 13,792 observations. The results indicated age exhibited a U-shaped relationship with life satisfaction, whilst being married, number of children, years of schooling, household income per capita, the importance of religion to an individual, and Body Mass Index (BMI) were all found to be positively associated with life satisfaction. Bookwalter and Dalenberg (2004) instead utilised a cross-section of 5,190 individuals from the South African Labour and Development Research Unit (SALDRU) survey conducted in 1994. The study assessed the differences in the relationship between life satisfaction and various socioeconomic factors between expenditure quartiles. The results highlighted that better housing and sanitation, along with reduced reliance on public transport, were significant determinants of life satisfaction for the poorest expenditure quartile. The authors noted many of these important determinants of life satisfaction had a public good component, meaning improving them is largely outside the households' control. Conversely, wealth and health were found to be significant positive determinants of life satisfaction for the richest expenditure quartile. The authors postulated this may be due to greater health awareness amongst the richest group.

Kannemeyer (2016) built upon prior research by utilising panel data from the first four waves of NIDS (2008 to 2014/15) to examine the determinants of life satisfaction in South Africa. In

addition to standard socioeconomic factors, the study considered neighbourhood attachment and perceptions of social disorder. The study had a substantial sample size of 34,634 observations. The findings indicated neighbourhood attachment and lower perceived disorder were positively associated with life satisfaction. Socioeconomic characteristics such as income per capita, perceived SES, employment, marriage, and better self-rated health were found to be positively associated with life satisfaction. Significant negative determinants of life satisfaction included CES-D 10 score (for which higher scores indicate greater presence of depressive symptoms) and living in urban informal or tribal areas relative to urban formal areas. Finally, a U-shaped relationship between age and life satisfaction was found. However, it is important to note that despite using panel data, the study did not employ fixed-effects estimation to control for individual-level heterogeneity.

Finally, Ting *et al.* (2017) investigated the relationship between weather-induced transitory income changes, savings behaviour, and SWB in South Africa. The study utilised a dataset consisting of 31,319 observations from the first four waves of the NIDS. Daily weather data from 1979 to 2014, obtained from the European Centre for Medium-Range Weather Forecasts, were used to predict transitory income changes. Permanent income was estimated based on various household characteristics. Household consumption and savings were derived from information on income and expenditure. The results indicated increased saving from transitory income was associated with a 14% increase in the odds of a one-unit increase in life satisfaction. This result is important as it implies negative climatic shocks to transitory income may negatively impact individual's wellbeing through their impact on the individual's savings behaviour. In contrast, increases in savings from the permanent component of income did not significantly affect life satisfaction. This study's strengths included its use of panel data and robust analysis methods. Furthermore, as the income variables were proxied by either exogenous climatic factors or by household socioeconomic and demographic factors, it was unlikely that potential endogeneity between life satisfaction and income affected the results.

3.2.2 Studies on Other Low- and Middle-Income Countries

Given the limited literature on determinants of SWB in Sub-Saharan Africa, we subsequently reviewed studies using multinational data from other LMICs. Some of these also made comparisons with HICs.

Firstly, Ngamaba (2017) conducted a cross-sectional analysis across 59 countries, spanning Western and Eastern Europe, North and Latin America, Asia, Sub-Saharan Africa, the Middle East, and Australia. SWB was assessed using two measures: life satisfaction on a 10-point scale

and a 4-point happiness scale. The study revealed significant positive determinants of SWB included health, financial satisfaction, higher income, freedom of choice, trust, national pride, and the importance of friends and family. Whilst useful in providing an indication of determinants of SWB across both LMICs and HICs, the cross-sectional data means causality could not be established.

Howell and Howell (2008) conducted a meta-analysis to investigate the relationship between socioeconomic status with SWB across 56 developing countries. Analysing 111 independent samples, they found the relationship between socioeconomic status and SWB was strongest in low-income countries with lower levels of education but weaker in high-income countries with higher education levels. The robustness of these findings was illustrated by the authors through analysing a sample of 102,224 observations from 54 LMICs across three waves of the World Values Survey (WVS). However, causality remained unestablished due to its cross-sectional nature.

Finally, Sarracino (2010) also examined SWB determinants in both low- and high-income countries using data from four waves of the WVS. SWB was primarily assessed using a 4-point happiness scale, with robustness checks using a 10-point life satisfaction scale. The results indicated that both absolute and relative income were positively associated with SWB in both low- and high-income countries, with a stronger effect in low-income nations. Social class and education also exhibited more pronounced impacts in LMICs. The positive association between marriage and SWB was stronger in HICs, whilst the negative relationship with divorce and widowhood was more significant in LMICs. Social capital, including participation in organisations, held greater importance for SWB in HICs. Unemployment was found to negatively correlate with SWB, but with a significantly stronger relationship in HICs. Gender showed consistent negative associations with SWB in both groups, and the U-shaped relationship between age and SWB occurred at a slightly later age in HICs. Whilst these findings illustrated differences in SWB determinants across income levels, they were constrained by the study's cross-sectional nature, calling for longitudinal investigations to deepen our understanding of SWB dynamics in these contexts.

3.3 The Relationship Between Shocks and Welfare Outcomes in Low- and Middle-Income Countries

3.3.1 Shocks and Subjective Wellbeing

In this sub-section, we explore the existing literature on the relationship between shocks and subjective wellbeing (SWB) in LMICs. While most studies did not exclusively focus on shocks, they integrated shock-related variables within broader analyses of SWB determinants. Only one study utilised data on Tanzania, whilst five studies examined data from South Africa. A further

two studies used data from Ethiopia, while one was a multinational study incorporating data from LMICs across a number of regions.

Firstly, Jiao *et al.* (2019) conducted a study in the Serengeti-Masa protected area, covering parts of Tanzania and Kenya. The authors primarily investigated the relationship between household environmental income, environmental reliance, and SWB. However, the analysis included an indicator for the number of (unspecified) self-reported shocks experienced by the household in the past 12 months. The data was drawn from 985 households across 25 rural villages. SWB was measured across five domains and an overall wellbeing index. Their findings indicated increasing numbers of idiosyncratic shocks experienced by households were negatively associated with overall wellbeing, as well as satisfaction in domains such as 'Basic Materials for a Good Life', 'Security', 'Health', and 'Freedom of Choice and Action'. Interestingly, households reporting more shocks also exhibited lower levels of absolute environmental income and a reduced reliance on environmental income. Although not suggested by the authors, the latter result may indicate households who experience more shocks may choose to rely on non-environmental sources of income as these are less susceptible to variations induced by the shocks. As with many of the preceding studies on the determinants of SWB in Sub-Saharan Africa, the findings of the study were limited by the non-representative cross-sectional sample utilised for the analysis.

Jansen *et al.* (2015) investigated multi-faceted poverty in South Africa using a sample of 16,883 individuals from the 2010/11 NIDS. The analysis included an indicator for experience of one or more negative events in the past year, including crop or livestock disease, serious illness or injury of a household member, and death of a non-resident family member. One measure of poverty utilised was life satisfaction, with individuals scoring 4 or below on a 10-point scale considered as being in 'poverty'. Using Probit regression, the authors found experience of negative events was unexpectedly associated with a lower probability of poverty based on life satisfaction scores. However, these negative events were positively associated with self-perceived relative poverty and other measures based on self-perceived relative welfare. Individuals reporting a high likelihood of being victims of crime also exhibited lower life satisfaction scores. Overall, the study was limited by only examining one wave of the NIDS, and by the uninformative negative events variable which only indicated that the household experienced at least one of many different negative events, rather than differentiating between events.

Moller (2005) explicitly examined the impact of one type of self-reported shock, being a victim of crime, on SWB in a sample of 3,300 households from the Nelson Mandela Metropolitan Municipality of South Africa. Victimisation of crime was measured by individuals reporting if their

household or members had experienced a burglary, theft of a vehicle, stock theft, theft out of a vehicle, and murder between 1998 and 2002. Household members were also asked if they personally had been a victim of robbery, assault, car hijacking, or sexual assault. Life satisfaction was utilised as the main outcome of interest. Not being a victim of crime was a positive predictor of life satisfaction. However, feelings of personal safety and freedom from the fear of crime were even more influential in improving life satisfaction than the absence of victimisation itself. This suggests fear of crime may be more detrimental to wellbeing than actual victimisation.

Alem and Kohlin (2014) investigated the impact of a food price inflation shock on life satisfaction in 706 urban Ethiopian households from the 2008/9 wave of the Ethiopian Urban Socioeconomic Survey (EUSS). Since the food price inflation was shock common to all households, the authors were not able to use an objective measure due to the cross-sectional data. Instead, a subjective question asking households if their consumption has been affected by the food price inflation the country experienced between 2007 and 2008 was utilised, with respondents given the option of "Very negatively", "Negatively", or "Not at all". The study found a strong negative association between perceived food price inflation and life satisfaction. Additionally, the study found receiving international remittances was positively associated with life satisfaction, potentially alleviating the negative SWB impacts of food price inflation. However, this was not empirically tested using interaction terms. As with Moller's (2005) study, this study was useful as it examined a specific shock as a determinant of SWB, rather than grouping multiple shocks together.

Reyes-Garcia *et al.* (2015) examined SWB determinants in sample of 6,973 individuals residing in rural areas across 23 developing countries, including various African nations. Whilst the authors were primarily interested whether absolute income matters more to the SWB of individuals at low-income levels, the analysis included shock variables indicating whether the household suffered a major loss of crops and/or livestock, a member of the household became recently unemployed, or a household member died or was seriously ill in the previous 12 months. Their findings revealed that major shocks, such as a loss of crops and/or livestock and household death or illness, were significantly negatively associated with life satisfaction. The impact of a household death or illness was particularly pronounced. However, becoming recently unemployed was not significantly related to life satisfaction. This study highlighted the importance of considering different types of shocks in SWB research, but the findings were limited as the authors did not calculate the average marginal effects (AMEs) from the ordered logistic regression and thus did not provide clear information on the magnitude of the associations between the shock variables and life satisfaction.

To summarise, much of the existing literature has not explicitly focussed on the impact of self-reported shocks on SWB, but rather has included shock-type variables as control in wider analyses. As such, many of these variables used to capture shocks were relatively uninformative. Those which did explicitly explore different shocks remained methodologically limited by cross-sectional data. The findings between studies were not conclusive, with negative, non-significant, and even unexpected positive relationships with SWB found. This clearly indicates that more research is needed into the impact of household shocks on SWB in LMICs using more robust methods.

3.3.2 Shocks and Mental Health

The preceding sub-section indicated there is conflicting evidence for the impact of shocks on SWB in the existing literature, which is also methodologically limited by the shock variables utilised in the analysis and the use of cross-sectional data. Considering this, we now turn papers utilising the closely related concept of mental health as an alternative outcome measure with African samples.

Firstly, Hamad *et al.* (2008) conducted an analysis of depressive symptoms and perceived stress using a small sample of 257 South African residents from Cape Town, Port Elizabeth, and Durban collected in 2004. The study included major life events which have occurred in the last 12 months as determinants of depressive symptoms and stress. These events were 'birth', 'catastrophe' (which includes fire or floods), and 'other' (which includes weddings, funerals, theft, and initiation ceremonies). The results revealed catastrophe, birth, and other events were positively associated with depressive symptoms, while catastrophe and birth were also positively associated with perceived stress. While these findings suggest negative shocks may contribute to depression, causal inferences were limited due to the cross-sectional nature of the data and the small sample size, representing only three regions of South Africa.

Dowdall *et al.* (2017) employed a larger, nationally representative sample of 11,995 individuals from the first wave of the South African NIDS. Their primary focus was on the relationship between neighbourhood-level deprivation and depression, with negative events included as a control variable. The negative events variable indicated whether an individual had experienced at least one of 11 listed negative events in the past year, such as crop or livestock disease, serious illness or injury of a household member, and death of a non-resident family member. This variable was interacted with overall and sub-domains of deprivation to explore whether deprivation's influence on depression varies with the presence of negative events. In contrast to Hamad *et al.* (2008), this study did not find an association between negative events and depressive symptoms, nor did it observe an interaction effect with overall deprivation. While this study improved upon the Hamad *et al.* (2008) by utilising a larger, nationally representative sample, it was still constrained by cross-

sectional analysis, and lacked a discussion of why the negative events variable did not exhibit an association with depression.

Alloush (2018) investigated the simultaneous relationship between 'psychological wellbeing' (measured by depressive symptoms) and 'economic wellbeing' (measured by household income per capita) using a balanced panel of 6,975 individuals from the first four waves of the South African NIDS (2008 to 2015). The study first identified a simultaneous positive relationship between psychological and economic wellbeing. Furthermore, the analysis explored whether this dynamic and bidirectional relationship between depression and income amplified the impact of shocks over time on future psychological wellbeing and income. Structural vector auto-regressions (VAR) were employed to estimate a Wold decomposition of a two-equation system of depressive symptoms and individual income. This allowed the effects of shocks on either psychological or economic wellbeing to be estimated over time. The study found that relative to a model where income and depressive symptoms follow unrelated processes, the bidirectional relationship accentuated the impact of negative income or depression shocks on future incomes and depression scores. Over time, the total impact of these shocks increased significantly. For instance, a shock to income, within the context of this bidirectional relationship, nearly doubled the total impact on future economic and psychological wellbeing. The study also conducted simulations to model the impact of this bidirectional relationship on poverty rates, relative to a model where depression did not influence income, and incorporated income shocks into the simulations to examine their effect on poverty rates. The findings of this are discussed in the next sub-section.

3.3.3 Shocks and Economic Welfare Outcomes

The existing literature on the relationships between shocks, SWB, and mental health is often methodologically weak. As such, we subsequently examined studies which have explored the relationship between various types of shocks and other economic welfare outcomes, including consumption, poverty, and food security. These generally employed more robust estimation techniques, and the findings were also useful as they provide information potential indirect pathways between shocks and SWB. Many of the studies examined a mix of idiosyncratic (affecting only the household) and covariate (affecting multiple households in an area) shocks, as well as exploring coping strategies utilised by households. Studies using data from African countries are presented first, followed by those using data from other LMICs.

3.3.3.1 African Countries

Firstly, we report the findings from the aforementioned study by Alloush (2018) using South African data on how shocks to income affect poverty rates. The study employed a simulation

approach, randomly generating income and depression scores at time 0 based on means and variances from the first four waves of the NIDS dataset. The model incorporated the previously identified bidirectional relationship between income and depression and compared poverty rates over time in scenarios with income shocks at time 0 of 20% and 50% to a scenario with no income shocks at time 0. The findings revealed that in the aftermath of an income shock, overall poverty rates increased. Notably, individuals assigned depression scores indicative of likely clinical depression at the simulation's outset exhibited poverty rates nearly 20% higher than those with low depression scores by the fifth period of the simulation. This suggested individual with high levels of depressive symptoms had lower resilience to income shocks. However, it is important to note this analysis was simulation-based, relying on hypothetical shocks derived from NIDS data. Subsequent studies reviewed explored actual shocks experienced by households using regression methods.

Harrower and Hoddinott (2004) conducted and analysis on the impact of self-reported idiosyncratic shocks and covariates shocks on consumption. The study encompassed panel data on 275 households from 10 villages in Mali surveyed over four rounds between 1997 and 1997. They found covariate shocks, represented by non-specific village-round dummy variables in the regression specifications, significantly reduced consumption. Surprisingly, idiosyncratic shocks, including illness, livestock theft, crop disease, and land cultivation issues, were not significantly associated with reduced consumption. To explain this, the authors estimated different coping strategies as a function of the idiosyncratic shocks. Differences in the coping strategies were found between asset-poor and asset-nonpoor households. Asset-poor households relied more on remittances, outmigration, and community-level risk-pooling. Contrastingly, asset-nonpoor households showed no evidence of risk-pooling and were more likely to use more autarkic methods of coping such as credit and income diversification. Although the study does make use of fixed-effects regressions for the analysis, it was limited by its small sample size, the short time frame of the panel, and the fact the data was relatively old.

Dercon and Krishnan (2000) also explored the impact of both self-reported idiosyncratic and observed village-level covariate shocks on consumption in rural Ethiopian households. Their study included a panel of 1,450 households surveyed over three rounds spanning 18 months, from 1994 to 1995. The results showed below-median village-level rainfall and self-reported crop and livestock shocks were negatively linked to consumption. The coefficients on all other shocks, including loss of working days due to illness, were not significant. In addition, household consumption exhibited seasonal patterns, increasing during the post-harvest peak labour period, and declining with seasonal food price increases. These findings suggest households were either

unable or unwilling to smooth consumption in response to shocks and seasonal variations. The study's strength lay in its use of fixed effects estimation, which accounted for unobserved time-invariant heterogeneity.

Porter (2012) utilised data from the Ethiopian Rural Household Survey (ERHS) to investigate the relationship between self-reported idiosyncratic and observable covariate shocks on consumption. The dataset included observations from 1,477 households spanning five waves, from 1994 to 2004. The idiosyncratic shocks included household perceptions of rainfall variation, crop disease, illness in the family, household deaths, and change in household head (a proxy for death or divorce). Village-level rainfall was also included, with rainfall quintiles across the data constructed. Dynamic generalised method of moments (GMM) and system GMM models were estimated, finding that households residing in villages in the bottom rainfall quintile exhibited significantly lower consumption. Surprisingly, illness among household members was positively correlated with consumption, although this was only statistically significant in the dynamic GMM model. A change in household head from male to female was found to be negatively associated with consumption. No other self-reported shocks were significant associated with consumption. Finally, the authors showed low (high) rainfall was associated with reduced (increased) crop income. Crop shocks were also found to significantly reduce crop income. Furthermore, better rainfall was negatively associated with non-farm income, whilst crop shocks were positively associated with non-farm income. The authors suggested this indicated households responded to rainfall and crop shocks by diverting their labour supply to non-farm activities. Thus, households were generally able to smooth their consumption in response many idiosyncratic shocks but could not fully insulate consumption against environmental or agricultural shocks. The study was strengthened by using the GMM estimator to control for endogeneity.

A different way in which the impact of shocks may be mitigated is through social safety net programmes. Bene *et al.* (2012) examined the effectiveness of Ethiopia's 'Productive Safety Net Programme' (PSNP) in safeguarding households' food security and self-reported economic wellbeing against various shocks reported to have occurred in the past 5 years. These included drought, flooding, loss of crops, loss of livestock, high agricultural input prices, low output prices, illness of household members, and other idiosyncratic shocks (death of household member, disability, theft, and break-up of the household grouped together). The study involved propensity score matching (PSM) 960 PSNP beneficiary and non-beneficiary households from the 2006 and 2008 waves of the 'Trends in Transfers' study. The analysis then compared difference in mean outcomes between the two groups. While beneficiary households generally exhibited greater food security and economic wellbeing, these differences were often not statistically significant.

Furthermore, households affected by shocks, including drought and crop loss, showed lower food security and economic wellbeing irrespective of beneficiary status. PSNP-beneficiary households which did and did not experience a shock were then matched via PSM. This showed households who experienced drought and higher agricultural input prices had significantly lower means levels of economic wellbeing. Households exposed to droughts, illness, and other idiosyncratic shocks also had significantly higher mean levels of food insecurity. This indicated that being a PSNP beneficiary did not fully insulate economic wellbeing and food security from some shocks. Subsequent analysis indicated all the shocks were associated with reduced food and/or non-food consumption. Coping strategies in response to shocks included selling livestock, withdrawing children from school, and reducing consumption. The findings were limited by a lack of regression-based analyses, instead relying on comparisons of means and controlling for confounders through PSM.

In Section 3.3.1, we discussed Alem and Kohlin's (2014) findings that Ethiopian households who reported being affected by high food price inflation in 2008 exhibited significantly lower levels of life satisfaction. Alem and Soderbom (2012) instead examined the impact of high food price inflation on food consumption in Ethiopia in two waves of data from 2004 and 2008. As 2008 was characterised by high food price inflation, the analysis utilised a dummy variable for the 2008 waves as an 'objective' measure of a food price shock and estimated a pooled regression with fixed effects. This indicated the food price shock had heterogeneous effects on food consumption across different groups. For instance, public sector and casual workers, female-headed households, and asset-poor households experienced more significant declines in food consumption during the crisis. Conversely, households with more substantial assets were better equipped to protect their food consumption levels from the shock's adverse effects. The study also employed subjective measures, utilising information from households in the 2008 wave regarding how negatively they perceived the food price inflation shock. These subjective measures yielded results consistent with the objective measures, reinforcing the finding that households with fewer assets and uncertain labour market status were particularly vulnerable to food consumption reductions during the crisis. The analysis also included self-reported shocks including death of a family member, illness of a family member, job loss of a family member, and asset loss, however these were not found to be significantly associated with food consumption.

Finally, d'Errico *et al.* (2018) investigated the impact of various shocks on food security using data from the Tanzania National Panel Survey (TZNPS) and the Uganda National Household Survey. Covering a period from 2008/2009 to 2012/2013, the study encompassed 2,866 households from the TZNPS and 2,031 households from the Uganda National Household Survey. Food security

was assessed through objective measures, including daily per capita caloric intake and the Simpson index, which evaluates dietary quality, as well as subjective measures. Binary indicators were constructed for reduced caloric intake and dietary diversity between survey waves. The analysis considered a range of shocks, including agricultural, climatic, labour market, health, and crime-related shocks. Additionally, exogenous covariate shocks were derived from data on vegetation, weather conditions, and conflict intensity. The latter was measured through a 'Conflict Intensity Index' (CII) derived by Bozzoli *et al.* (2011). Probit regression analysis revealed that while exogenous natural shocks, such as high rainfall and flooding, adversely affected food security, self-reported shocks did not significantly influence food security outcomes. This was converse to Bene *et al.*'s (2012) findings in Ethiopia. The study was methodologically limited as the use of Probit regression precluded the possibility of controlling for fixed effects. As such, unobserved heterogeneity may have biased the results.

3.3.3.2 Other Low- and Middle-Income Countries

Akter and Basher (2014) investigated the impact of escalating global food prices on food security and household expenditures in rural Bangladesh, employing data from 1,810 households collected in two waves, 2006/07 and 2009/10. Food insecurity was assessed through self-assessments, with households required to identify the month and year of their worst food shortage incident (if any) between 2007 and 2009. Food expenditure served as an objective measure. The study considered both positive shocks (*e.g.*, remittances) and negative shocks (*e.g.*, self-reported losses due to flood or non-flood damage), alongside spatially disaggregated monthly rice price data matched to households. Multinomial logistic regression revealed higher remittances in 2008 reduced the likelihood of households reporting their worst food shortage that year, whereas greater losses or damages in 2008 and 2009 increased this likelihood. The study also found the probability of food insecurity increased more than proportionately with increased rice prices. Findings also indicated that poorer households with fewer assets and land, and lower household expenditure were more likely to report being food insecure. This contributes to evidence presented by Alem and Soderbom (2012) that food price inflation may have heterogeneous impacts on food insecurity between different groups in a population. Analysing the effects on household expenditure per capita, the study found that experiencing food shortages in 2007 was negatively associated with expenditure growth. However, despite 2008 being the peak of food price inflation, no such association was found in this year. Negative income shocks had no significant impact on expenditure, while positive shocks, such as remittance growth or new receipt of government transfers, positively affected expenditure. The finding that negative idiosyncratic income shocks were unrelated to total household expenditure is largely consistent with other studies.

Skoufias (2003) conducted an analysis of the impact of job loss and other labour market shocks on consumption using data from the Russian Longitudinal Monitoring Survey (RLMS) collected between 1994 and 2000, comprising 14,097 observations across five waves. The study examined various labour market shocks, including wage arrears, forced leave from work, and unemployment, and assessed their effects on total consumption, food consumption, and non-food consumption while controlling for socioeconomic factors and community-year controls. The results indicated that in urban households, the incidence of wage arrears and unemployment between survey rounds had a negative association with the growth rate of total consumption, while forced leave was not significantly related to consumption. Job loss had a negative impact on both food and non-food consumption, with a greater effect on non-food consumption. Wage arrears were also negatively associated with non-food consumption but not with food consumption. Interestingly, urban households seemed to prioritise food consumption and reduce non-food consumption in response to shocks. In rural areas, none of the shocks were significantly related to any consumption outcomes, suggesting rural households were better able to cope with these shocks. The study also found individuals employed different coping mechanisms in response to different shocks. For instance, households with wage arrears relied on debt, while those on forced leave were more likely to seek a second job or engage in agricultural activities. Households with unemployed members instead resorted to transfers, borrowing, and asset sales. Additionally, the study identified a positive relationship between household consumption and community-level income, suggesting community risk-pooling was a coping strategy. However, it should be noted the study's methods did not account for unobserved heterogeneity through fixed effects, and the sample was relatively dated.

3.4 The Relationship Between Food Insecurity and Subjective Wellbeing

The literature reviewed in sub-section 3.3 suggests there may be a connected relationship between shocks, food insecurity, and subjective wellbeing. This sub-section provides an overview of research on the direct relationship between food insecurity and SWB. Numerous studies have employed the Gallup World Poll, an annual multinational survey with nationally representative samples from countries worldwide. In this, SWB is assessed through life evaluation on an 11-point scale, alongside the administration of the Positive and Negative Experience Indices (PEI and NEI), which have alternatively been taken as measures of positive and negative affect, or positive wellbeing and mental health. Food insecurity is gauged using the Food Insecurity Experience Scale (FIES) from the Food and Agriculture Organisation (FAO), inquiring whether respondents experienced eight increasingly severe food insecurity situations in the past year. The sum of 'yes'

answers provide the raw FIES score, which can be adjusted using different thresholds for countries to represent varying food insecurity levels.

Firstly, in a study encompassing 132,618 observations across 138 countries from the 2014 Gallup World Poll, Frongillio *et al.* (2017) demonstrated food insecurity was the most significant predictor of SWB, surpassing all other socioeconomic determinants. This study also revealed that the impact of food insecurity on wellbeing increased with higher World Bank income classifications, suggesting a more substantial impact in wealthier countries. Elgar *et al.* (2021) extended this work by using six rounds of the Gallup World Poll from 2014 to 2020, incorporating the Yitzhaki index of relative deprivation to produce a measure of relative food insecurity, whereby raw FIES scores (absolute food insecurity) of individuals were weighted relative to individuals within the same deprivation group. Their results showed relative food insecurity exhibited a stronger association in countries with a lower prevalence of food insecurity. In fact, in countries with a high prevalence of food insecurity, relative food insecurity was not significantly associated with wellbeing at all. The authors suggest this finding indicates the relationship between food insecurity and poorer wellbeing may be intensified in countries with a low prevalence due to food insecure individuals making unfavourable social comparisons to others in their socioeconomic group.

Na *et al.* (2018) instead focused on 39 Sub-Saharan African countries in the 2014 to 2016 rounds of the Gallup World Poll to investigate the moderating role of different forms of social support in the relationship between food insecurity and SWB. They found increasing food insecurity severity correlated with higher NEI scores and lower PEI scores. Moreover, the NEI scores were lower and PEI scores were higher across all levels of food insecurity for individuals with greater social support. This modifying effect of social support was most pronounced among those facing severe food insecurity, supporting the stress-buffering model.

Asfahani *et al.* (2019) explored the link between food insecurity and SWB in 19 Arab countries from the 2014 and 2015 Gallup World Poll rounds, considering varying levels of political stability. The study used the World Bank's 2014 Political Stability and Absence of Violence and Terrorism (PSAVT) score. Their findings, consistent with previous studies, revealed moderate and severe food insecurity were negatively associated with positive wellbeing measures. Interestingly, the strength of these associations varied based on the level of political stability. Moderate food insecurity had the smallest (absolute) coefficients in countries with low political stability but the largest in those with medium political stability, while severe food insecurity exhibited the opposite trend. However, the authors provided limited explanation for these findings.

In summary, studies utilising Gallup World Poll data consistently found a negative relationship between food insecurity and wellbeing. However, due to the highly aggregated nature of this data, these studies often lacked in-depth exploration of the underlying mechanisms. Addressing this, Hadley *et al.* (2012) adopted a qualitative approach in Ethiopia's Jimma province to investigate the impact of rapidly rising food prices on food security, health, and SWB. Conducting twenty semi-structured interviews in August 2011, they found participants reported experiencing significant price increases in core food items. Participants also reported stress due to financial concerns and constant worry about their next meal. Additionally, many reported feeling ashamed for being unable to provide sufficient food for their children and when their children sought food from neighbours. Sleep loss, concerns about perceptions by children and neighbours, and reduced participation in cultural food-sharing traditions added to stress. Households employed various coping strategies, including reduced dietary diversity, using savings, selling assets, or borrowing money. These findings help explain why food insecurity negatively affects SWB, as seen in Gallup World Poll studies, though we should be cautious in generalising these findings given the small sample size and specific context in Ethiopia.

Finally, Trudell *et al.* (2021) conducted a systematic review on the relationship between food insecurity and mental health in Africa, including 35 studies from East Africa (of which two were conducted in Tanzania with pregnant women). The study found a consistent negative link between food insecurity and mental health. The review also highlighted that more severe food insecurity exhibited stronger associations with mental health outcomes. Factors such as gender, age, and social support were identified as mediators in this relationship. Women's mental health was more negatively impacted by food insecurity, possibly due to their limited autonomy over resources in patriarchal societies. However, the authors stressed male mental health was still significantly affected by food insecurity, perhaps reflecting perceived failure to live up to the role of being a provider for their families. Older adults experiencing food insecurity were often found to exhibit a stronger relationship with poorer mental health outcomes, likely due to limited mobility, lower income, poor physical health, and material deprivation. Social support mitigated the mental health impact of food insecurity, particularly in severe cases. However, the review noted limitations in the small-scale, specific population-based samples of the studies reviewed and recommended future research with larger, population-based samples to further investigate the relationship between food insecurity and mental health and wellbeing outcomes in Africa.

3.5 The Relationship Between Conflict, Subjective Wellbeing and Other Welfare Measures

This subsection begins by exploring the existing literature on the relationship between conflict and SWB. As relatively few papers were identified, we subsequently present two additional studies which explored the relationship between conflict and other welfare measures. Both utilised the conflict data from the Armed Conflict Location Event Data (ACLED) Project.

3.5.1 Conflict and Subjective Wellbeing

Welsch (2008) examined the impact of conflict on SWB in 21 countries involved in civil conflict in the year 2000, including various countries from Africa, South America, Asia, and Europe. Two datasets were combined for the analysis, the Upsala Conflict Data Base (UCDB), and the World Database of Happiness. The author utilised average national SWB as the outcome variable, which was estimated as a function of the number of civil war-related deaths per capita (capturing conflict intensity), GDP per capita, and other national-level sociodemographic, institutional, and economic controls. The number of civil war deaths was then replaced by the change in deaths from the previous year. The results indicated both the number and change in deaths were significantly negatively associated with SWB, with the latter exhibiting a stronger relationship. The author suggested this indicates it was the initiation or intensification of conflict that had a particularly strong impact on national SWB.

The author subsequently noted that since GDP per capita was included as a covariate, the models captured the direct non-pecuniary impact of conflict on SWB. However, they proposed that conflict may also have an indirect impact on SWB through a negative impact on income. To investigate this, GDP per capita was replaced with capital per capita, and the models were re-estimated. The estimated coefficients were larger (in absolute terms) for both the number and change in victims. This was interpreted as indicating that both the level of conflict and an increase in conflict appear to have a direct and indirect impact on national SWB. However, the estimates indicated the direct impact (*e.g.*, suffering, fear, and altruism) was stronger than the indirect impact through reduced income. Although the generalisability of the findings of the study was strengthened by the diverse range of countries considered, it was also limited by only considering one year of data, and subsequently having a low sample size for the analysis.

Shemyakina and Plagnol (2013) instead utilised a larger sample of panel data consisting of 9,4000 observations on individuals from 2001 to 2004 from the Living in Bosnia and Herzegovina Survey to investigate the relationship between SWB and armed conflict in Bosnia-Herzegovina following the 1992-1995 Bosnian War. SWB was measured through life satisfaction on a 7-point scale; however, this was only available from the 2002 wave onwards. Several measures of conflict

exposure were utilised. The first was a binary variable capturing if the respondent reported their home has war damage. The second was based on war-related trauma, with individuals asked how frequently in the last week they recalled the most painful events they experienced during the war. Four responses were possible, ranging from "Not at all" to "Extremely often". This variable was not available in the 2002 wave. In addition to the individual-level conflict measures, the authors incorporated information on municipality-level conflict from the Bosnian Book of Dead Project (1991-1995). This was utilised to calculate the municipality-level casualty rate, which was then matched to the individual-level data.

First, repeated cross-section models were estimated for each of the waves from 2002 to 2004. The results showed neither of the municipality-level conflict measures were significantly associated with life satisfaction in any of the waves. However, reporting a war-damaged dwelling or increasing war trauma were significantly negatively associated with life satisfaction. Using fixed effects models, the authors then found life satisfaction declined in 2004 relative to 2002 in municipalities with a higher casualty rate. However, the authors noted that since they could not control for municipality-level economic conditions, this may reflect that municipalities with higher casualty rates in the war tended to have poorer economic conditions resulting from the war. The war trauma variable was again found to be negatively associated with life satisfaction, although the estimated coefficient was smaller than in the cross-sectional analysis, indicating the importance of controlling for individual-level time-invariant heterogeneity through fixed effects. Although the study provided a unique insight into the relationship between various measures of conflict and SWB using panel data, one of its limitations was that the municipality-level conflict measure was based solely on the casualty rate in a single year, which was several years prior to the household data. Thus, the study did not provide insight into the potential impact current conflict may have on SWB.

Finally, Wills-Herrera *et al.* (2011) explored the relationship between subjective perceptions of civil insecurity and SWB using evidence from an area of rural conflict in Colombia. The paper also investigated whether social capital moderated any relationship found between perceptions of insecurity and SWB. The data consisted of 742 observations on owners or managers of productive properties across five rural geographical regions in 2006. The five regions were selected to represent differing objective insecurity levels, with this based on an index reflecting the number of homicides, kidnappings, armed clashes, and displaced people per 100,000 inhabitants in the past 5 years. SWB was measured using the Personal Wellbeing Index (PWI). Perceptions of insecurity were measured across four different domains – perceptions about personal safety (PERINS),

perceptions about political freedom of voice and expressions (POLINS), perceptions of economic security (ECOINS), and perceptions of security provided by the community (COMINS).

The authors employed a multi-level estimation approach, including individual-level variables alongside municipality- and regional-level variables. This included the municipality-level objective civil insecurity index. At the individual level, three of the four perceptions of insecurity domains were significantly negatively associated with PWI (POLINS, ECOINS, and COMINS). The results then indicated some moderating impact of social capital whereby the SWB of those with low perceptions of insecurity was further enhanced for those with higher social capital. However, the objective index of insecurity measured at the municipality level was not significantly associated with SWB. This suggests that perceptions of civil insecurity may be more important to SWB than the objective level of insecurity. However, the findings were limited by the cross-sectional data, meaning the econometric models could not control for unobserved heterogeneity.

3.5.2 Conflict and Other Welfare Outcomes

Bozzoli *et al.* (2011) conducted a study on the impact of war on individuals' expectations regarding future welfare. The authors analysed cross-sectional data from approximately 3,600 households in the 2007 Northern Uganda Livelihood Survey. Respondents were asked if they believed their economic situation would improve in the future (coded as 1 for "Yes" and 0 for "No" or "Don't know"). They were also questioned about whether they expected their life to be "Better than now", "Of the same quality", "Worse than now", or "Don't know" in one year's time (coded as 1 for positive expectations and 0 otherwise). The researchers used data on conflict events from the ACLED Project to construct the Conflict Intensity Index (CII) for 2002 and 2006, covering the period when Uganda was at war. The CII captured geographically discounted conflict events for each household based on their proximity to all events recorded in the given years.

The 2002 CII was found to be weakly positively associated with future economic expectations, while the CII for 2006 was strongly negatively associated with these expectations. This suggested recent exposure to conflict led to pessimistic expectations about future economic circumstances. Conversely, the 2002 CII was negatively associated with general life expectations, while the 2006 CII coefficient was not statistically significant, indicating past conflict more strongly influenced individuals' expectations about their general life quality. This disparity between the two types of expectations could be due to economic situations improving faster than overall life quality after a conflict, with the latter being influenced by the psychological and health impacts of war. However, these findings were limited by the cross-sectional nature of the data, which made it challenging to control for unobserved heterogeneity and observe changes in expectations over time.

Finally, Dabalen and Paul (2014) estimated the impact of conflict on dietary diversity, a measure of food insecurity, in the Ivory Coast. The authors used data from two rounds of the repeated cross-sectional survey Enquête sur le Niveau de Vie de Ménages (ENV). The first round, ENV-2002, represented the pre-conflict period with approximately 10,800 households, while the second round, ENV-2008, represented the post-conflict period with around 12,600 households. Conflict data from the ACLED Project were merged with household data. Dietary diversity was measured using the food consumption score (FCS), which considered the frequency of consumption of eight food groups weighted by their nutritional density.

Regression-based difference-in-differences (DD) estimation firstly found that FCS fell significantly more in the Northern regions (with intense conflict) relative to those in the less-affected Southern regions. Subsequently, the authors used department-level conflict data to create a dummy variable indicating whether a department experienced at least one conflict event between 2002 and 2006. Regression analysis found a negative but statistically insignificant coefficient on the conflict dummy. However, it was noted food aid programs operated in Ivory Coast from the onset of the crisis until 2008, potentially biasing the causal effect of conflict on FCS. After dividing the sample into households from departments receiving food aid and those not receiving aid, a statistically significant negative coefficient for the conflict dummy was found in the food aid sample, indicating households in conflict-affected departments receiving aid were more likely to experience food insecurity. This suggested households in food aid departments experiencing conflict were significantly more likely to face food insecurity than those in non-aid departments. Finally, the authors explored the relationship between nine self-reported consequences of conflict and FCS, finding households reporting family deaths, income reductions, loss of property, job loss, or farm loss exhibited significantly lower FCS scores.

3.6 Summary and Contribution

The proceeding review highlighted a relative dearth in methodologically robust studies on the impact of shocks on SWB in LMICs. While four studies included a shock-related variable as a covariate in their analyses, their primary focus did not centre on the effects of shocks on SWB. Moreover, these studies often used limited shock variables, either condensing multiple potential shocks into a single binary variable or failing to specify the nature of the shocks (Jiao *et al.*, 2015; Jansen *et al.*, 2015). Consequently, results from these studies yielded varying outcomes, ranging from an unexpected positive association between the shock variable and life satisfaction to an anticipated negative relationship with a wellbeing index. Reyes-Garcia *et al.* (2015) improved on these studies by incorporating specific shock measures, discovering that major crop or livestock

losses and household deaths or illnesses were significantly negatively linked to life satisfaction. Two studies delved into specific types of shocks. Moller (2005) found that while actual victimisation of crime could explain some variance in the life satisfaction of South African individuals, fear of crime itself was a more substantial predictor of SWB. In addition, Allem and Kohlin (2014) demonstrated that a higher self-perceived impact of food price inflation in urban Ethiopian households correlated with lower life satisfaction. Given this paucity in the literature, we expanded our investigation to include studies considering mental health outcomes. Three South African studies incorporated shock variables into their analyses, yielding mixed results. Hamad *et al.* (2008) found that self-reported 'catastrophes' were positively associated with depressive symptoms, while Alloush (2018) indicated the bidirectional relationship between income and psychological wellbeing exacerbated negative income or depression shocks. Conversely, Dowdall *et al.* (2017) reported that self-reported experiences of negative events were not linked to depressive symptoms.

In contrast, the literature on shocks and economic welfare outcomes was more extensive, with numerous studies employing more robust econometric techniques and climatic data to supplement household panel data. Many of these studies investigated various shocks, which could be broadly classified as observable covariate shocks (*e.g.*, extreme weather fluctuations, food price inflation) and self-reported idiosyncratic shocks (*e.g.*, crop and livestock diseases, household member deaths or illnesses, labour market shocks). Observable covariate shocks typically exhibited negative associations with consumption and positive correlations with poverty and food insecurity (Dercon and Krishnan, 2000; Porter, 2012; d'Errico *et al.*, 2018). Some of these shocks affected different population groups disparately. Results for self-reported idiosyncratic shocks were more mixed. While some studies found no associations between self-reported idiosyncratic shocks and welfare outcomes, others identified negative relationships for specific shocks like household illness, recent job loss, wage arrears, and agricultural setbacks (Dercon and Krishnan, 2000; Skoufias, 2003; Bene *et al.*, 2012). Several studies further indicated that households frequently employed a range of strategies to mitigate the impact of various shocks (Dercon and Krishnan, 2000; Skoufias, 2003). Evidence also suggested that social protection programmes could safeguard other welfare outcomes against the effects of shocks (Bene *et al.*, 2012).

Subsequently, the literature concerning the relationship between food insecurity and SWB was examined. Four studies utilised the Gallup World Poll, a multinational survey with multiple cross-sectional waves. All four concluded that food insecurity significantly negatively predicted life evaluation and measures of positive affect (Frongillo *et al.*, 2017; Elgar *et al.*, 2021; Na *et al.*, 2018; Asfahani *et al.*, 2019). Furthermore, the strength of the negative link between food insecurity and

SWB was found to increase with a country's income level (Frongillo *et al.*, 2017) and decrease with the prevalence of food insecurity within a country (Elgar *et al.*, 2021). Na *et al.* (2018) further demonstrated that increasing levels of food insecurity were more strongly associated with poorer SWB, and that social support provided a protective mechanism for the relationship. Hadley *et al.* (2012) provided some insight into this relationship by conducting a qualitative study on a small sample of Ethiopian households, finding that food insecurity may directly impact SWB through the stress it induces and concerns about how families are perceived by their children and neighbours. Hence, existing literature suggests a robust negative relationship between food insecurity and SWB, although none of these studies used household panel data to examine this association.

Lastly, the relationships between conflict, SWB, and other welfare outcomes were explored. Studies generally indicated a negative association between conflict and SWB, although these were limited by using historical measures of conflict, or by using country-level aggregate measures of wellbeing (Welsch, 2008; Shemyakina and Plagnol, 2013). Given the relatively scarce literature on the topic of conflict and SWB, two additional studies were examined that employed other welfare measures as outcome variables. Both studies utilised the ACLED database. Bozzoli *et al.* (2011) found that their 'conflict intensity index' (CII) was negatively associated with future economic expectations and future life expectations in a sample of Ugandan households. Dabalen and Paul (2014) further demonstrated that dietary diversity was negatively impacted by conflict in the Ivory Coast.

Taken together, the existing literature suggests that there may be an intertwined relationship between shocks, conflict, food insecurity, and SWB. However, there has been little direct study of these interconnected relationships. Considering these research gaps, this paper contributes in the following ways. Firstly, it offers an in-depth exploration of the impact of shocks, food insecurity, and conflict on SWB. It advances the existing literature by utilising detailed variables related to various self-reported shocks and food insecurity using individual-level panel data from Tanzania. This approach aligns with recommendations made by Trudell *et al.* (2021) who advocated future studies to use large, nationally representative data to examine the influence of food insecurity on wellbeing measures in Africa. Additionally, this study constructs an objective measure of recent changes in conflict levels using ACLED Project data matched to households in the TZNPS. Robust panel data econometric techniques that account for unobserved heterogeneity are applied for the analysis. The analysis also explores potential moderators in the estimated relationships between shocks, food insecurity, and conflict on the one hand and SWB on the other, whilst mediation analysis examines food insecurity and consumption as potential mediators through

which shocks and conflict may influence SWB. Lastly, the preceding review highlighted that, to the best of our knowledge, no study has investigated the socioeconomic determinants of SWB in Tanzania using nationally representative panel data. Consequently, this analysis, through the inclusion of numerous socioeconomic controls, offers novel insights into whether socioeconomic factors are related to the SWB of the Tanzanian population over and above shocks, conflict, and food insecurity.

4. Hypotheses

The section presents the hypotheses tested in this paper. The first hypothesis specifies the expected relationships between self-reported household shocks, conflict, and food insecurity with SWB. The next set of hypotheses proposes the direction of moderation in these relationships by food insecurity (for shocks and conflict), consumption quartile, and receipt of government or NGO assistance. The final set of hypotheses pertain to the expected mediating role of food insecurity and consumption quartile (our measure of economic resources) in the relationships between shocks and conflict with SWB.

4.1 The Relationships between Shocks, Conflict, and Food Insecurity with Subjective Wellbeing

The experience of negative events such as death or illness of a family member, loss of employment, or damage to one's property would be expected to invoke negative emotional reactions in individuals. However, the existing literature on the impact of shocks on measures of SWB in LMICs did not provide consistent predictions for these relationships. That said, some studies were limited by uninformative measures of shocks (Jansen *et al.*, 2015; Jiao *et al.*, 2019), which likely contributed to the observed lack of concurrency in their findings. In studies conducted in Africa with more informative measures, shocks such as loss of livestock or crops, household deaths or illness, experience of crime, and food price inflation were found to be associated with lower levels of life satisfaction (Reyes-Garcia *et al.*, 2015; Moller, 2005; Allem and Kohlin, 2014).

Conversely, studies utilising multinational data from the Gallup World Poll consistently found evidence of a strong negative association between food insecurity and SWB (Frongillo *et al.*, 2017; Elgar *et al.*, 2021; Na *et al.*, 2018). Qualitative research conducted in Ethiopia corroborated these findings, indicating the significant role food insecurity plays in increasing stress and worry (Hadley *et al.*, 2012), whilst a systematic review indicated a consistent relationship between food insecurity and poorer mental health outcomes (Trudell *et al.*, 2021).

Finally, although relatively scarce, studies exploring the association between conflict and SWB tended to find a negative relationship in both single country and multinational data (Shemyakina and Plagnol, 2013; Welsch, 2008). Again, the experience of conflict events would be expected to reduce wellbeing of those affected given their unpleasant nature and the worry of the potential consequences and the potential consequences these events may have on individuals' livelihoods. Considering this, we proposed the following first hypothesis:

H1: Self-reported household shocks, conflict, and food insecurity are negatively associated with SWB.

4.2 The Moderating Role of Food Insecurity, Consumption Quartile, and Assistance

Given the limited existing literature on the relationship between shocks and SWB, there is relatively little evidence on factors which may play an important moderating role. However, it is reasonable to postulate food insecurity status may be a moderator. It is likely that those who are food insecure may already be struggling financially and already be under considerable stress (Hadley *et al.*, 2014), meaning the negative mental health effect of a shock may be compounded. Furthermore, several studies indicated that socioeconomic factors may moderate the relationship between shocks and other welfare outcomes (Alem and Soderbom, 2021; Trudell *et al.*, 2021). Indeed, we suspect that individuals with more economic resources would be better equipped to deal with the financial impacts of shocks, which may therefore provide some protection against their impact of SWB. Equally, Bene *et al.* (2012) showed that recipients of a government financial support in Ethiopia were less susceptible to the impact of household shocks on consumption. It is plausible that a similar protective effect may apply to SWB, with financial support providing a buffer against the economic stressors imposed by shocks. Similar logic can apply to reasons why these factors may moderate the relationship between conflict and SWB, with conflict episodes possibly imposing emotional and financial consequences which could be exacerbated by pre-existing food insecurity, and potentially protected against by greater economic resources be it the household's own finances or additional support provided by the government.

Finally, whilst the relationship between food insecurity and SWB clearly cannot be moderated by itself, we postulate that those who receive financial support may be protected from the negative wellbeing impact of food insecurity. Conversely, we postulate that individuals of a higher economic status may be more susceptible to negative mental health effects should they experience food insecurity. This proposal is based on findings from Elgar *et al.* (2017), who showed that relative food insecurity exhibited a stronger negative association with SWB in countries with less prevalence of food insecurity, suggesting this may be due to food insecure individuals making more unfavourable social comparisons in this context. We therefore test whether this translates to a within-country setting, whereby food insecurity is likely to be rarer amongst those with more economic resources, and thus when it does occur this may carry a greater social stigma amongst those affected. Furthermore, individuals of a lower economic standing may be 'used' to being food insecure, whereas for historically richer individuals, the experience of food insecurity may come as a greater shock, and they may be less versed in dealing with this experience. Considering this, we proposed the following as the second set of hypotheses. Note that the upper household consumption quartile was utilised as a measure of economic resources when testing *H2b*.

H2a: Food insecurity will negatively moderate the relationships between self-reported household shocks and conflict with SWB.

H2b: Consumption quartile will positively moderate the relationship between self-reported household shocks and conflict with SWB, and negatively moderate the relationship between food insecurity and SWB.

H2c: Governmental or NGO financial or other assistance will positively moderate the relationships between household shocks, conflict, and food insecurity with SWB.

4.3 The Mediating Role of Food insecurity and Consumption.

Finally, we tested for the mediating roles of food insecurity and consumption in the relationships between shocks and conflict with SWB. The existing literature on household shocks and other welfare outcomes indicated that observable covariate shocks were often negatively associated with consumption and positively associated with incidence of poverty and food insecurity (Dercon and Krishnan, 2000; Porter, 2008; d'Errico *et al.*, 2018), whilst some studies evidenced a negative relationship between idiosyncratic shocks such as household illness, recent job loss and incidence of wage arrears, and agricultural shocks, with economic welfare outcomes (Dercon and Krishnan, 2000; Skoufias, 2003; Bene *et al.*, 2012). Similarly, some preceding evidence indicated that conflict was associated with increased food insecurity (Dabalen and Paul, 2014), whilst more conflict affected areas also tend to be economically poorer (Shemyakina and Plagnol, 2013). Furthermore, Welsch (2008) found evidence using country-level data for both a direct and indirect effect of conflict on SWB, with this indirect effect coming through reduced national income. As such, it is plausible that should a negative relationship between shocks and conflict with SWB exist, this relationship may be partially mediated by the impact these shocks and conflict have on food insecurity and other economic outcomes such as consumption, which in turn are also expected to be significantly associated with SWB as outlined above. Thus, we proposed the following as the final set of hypotheses:

H3a: Food insecurity is a mediator of the relationships between household shocks and conflict with SWB.

H3b: Consumption is a mediator of the relationships between household shocks, conflict, and food insecurity with SWB.

5. Data and Descriptive Statistics

This section presents the data utilised in the analysis to test our hypotheses. Firstly, an overview of the Tanzanian National Panel Survey (TZNPS) is provided, followed by a description of the variables we drew from the survey for our analysis. Subsequently, we provide details of the Armed Conflict Location and Event Data (ACLED) Project (Clionadh *et al.*, 2010) and how we utilised this dataset in conjunction with the TZNPS. Table B1 in Appendix 1B provides detailed descriptions of how all variables we utilised were constructed. Finally, we present descriptive statistics for the sample utilised in the baseline analysis.

5.1 The Tanzanian National Panel Survey

5.1.1 Overview

The TZNPS is a panel dataset which forms part of the World Bank's Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA). LSMS-ISA are available on a total of eight Sub-Saharan African countries, with the TZNPS implemented by the Tanzanian National Bureau of Statistics (NBS) (World Bank, 2020).

The first wave of the TZNPS was collected in 2008/9, comprising a total of 3,265 households from mainland rural areas, Dar es Salaam, other mainland urban areas, and Zanzibar. A further three waves are currently available, conducted biennially for 2010/11, 2012/13, and 2014/15. The second wave expanded to consist of 3,924 households, and the third to 5,015 households, with these increases resulting from the split up of households from the preceding wave to form new households. For the fourth wave, the sample was refreshed to realign with changes in administrative boundaries and demographic shifts, resulting in a new sample consisting of 3,352 households (World Bank, 2020). In addition, a small sub-sample of households from the original three waves were selected to continue in the survey which form part of the wave four 'Extended Panel' (Tanzanian NBS, 2016). For each wave, detailed information is provided on individual's SWB, shocks experienced by their household, and socioeconomic and demographic characteristics. However, information on self-reported food insecurity was only collected from wave 2 onwards, whilst household consumption was not available in wave 4. Thus, we only utilised waves 2 and 3 of the TZNPS.

5.1.2 Subjective Wellbeing

SWB in the TZNPS was measured through life satisfaction. Specifically, each individual in a household was asked *"How satisfied or dissatisfied would you say you are with your life as a whole?"*. Responses were measured on a 7-point scale from 1 "Very satisfied" to 7 "Very dissatisfied". We reverse coded this scale for ease of interpretation.

5.1.2 Household Shocks

Extensive information is provided in the TZNPS on numerous possible shocks the household may have faced. Information on whether the household experienced any shocks was elicited through the following question:

"Over the past five years, was your household severely affected negatively by any of the following events?"

The household head was provided with a list of 18 shocks: "Droughts or floods"; "Crop disease or crop pests"; "Livestock died or were stolen"; "Household business failure (non-agricultural)", "Loss of salaried employment or non-payment of salary"; "Large fall in sale prices for crops"; "Large rise in the price of food"; "Large rise in agricultural input prices"; "Severe water shortage"; "Loss of land"; "Chronic/severe illness or accident of household member"; "Death of a member of the household"; "Death of other family member"; "Break-up of the household"; "Jailed"; "Fire"; "Hijacking, robbery, burglary, or assault"; "Dwelling damaged or destroyed". Households may also indicate if they experienced another shock which is not listed. As we consider both urban and rural households, we did not utilise the shocks pertaining to agriculture and the environment as these were not applicable to individuals residing in urban areas.

The household head was then asked to rank the three most significant shocks they experienced, and for these shocks provide the date when they occurred. This information was utilised to construct a series of indicators reflecting if the household head reported experiencing the shock within the previous two years, and if the shock was one of the three most severe they faced.

Specifically, we constructed the following measures reflecting the following six shocks: 'Large rise in the price of food', 'Chronic or severe illness or accident of household member', 'Death of household member', 'Death of other member of family', 'Hijacking, burglary or assault', and 'Break-up of household'. Due to the low prevalence of some of the shocks in the sample, two measures which grouped shocks together were also constructed: a 'Labour market shock' for households which reported experiencing "Loss of salaried employment or non-payment of salary" and/or "Household business failure", and 'Other idiosyncratic shock' for households who reported experiencing at least one of "Dwelling damaged or destroyed", "Fire", or "Jailed". Finally, we also considered a measure which reflected a 'Other unspecified shock' if the household reported experiencing any other shock not listed in the survey.

5.1.3 Food Insecurity

In waves 2 and 3 of the TZNPS, the household head was asked *"In the last 12 months, have you been faced with a situation when you did not have enough food to feed the household?"*, to which they can reply "Yes"

or "No". We considered household heads who reported "Yes" as experiencing self-reported food insecurity.

Additionally, waves 2 and 3 of the TZNPS collected detailed information on household food and non-food expenditures. We utilised this information to calculate the household's food to total expenditure ratio. This represented an approximation for the risk of a household being food insecure, with a higher ratio indicating a greater risk of food insecurity. Although there is no definitive threshold in the literature, Smith and Subandoro (2007) suggest a ratio of over 75% is indicative of a household being very high risk of food insecurity, whilst a ratio of 65% to 75% suggests a high risk of food insecurity.

5.1.4 Household Location

Information was provided on the location of the household, stratified by region, district, ward, and enumeration area. Additionally, offset latitude and longitude coordinates for the households were provided. Specifically, the TZNPS applied a random offset within a specified range to the average enumeration area value. For urban areas, a range of 0-2km was utilised, whilst for rural areas the range was slightly larger at 0-5km due to the more dispersed nature of rural communities. The offset was constrained such that the coordinates remain contained in the correct district. For more information, the reader is referred to 'Appendix A: Confidential Information, Geospatial Variables' of the 'Basic Information Document' provided by the TZNPS (Tanzania National Bureau of Statistics, 2014). The provision of these offset latitude and longitude coordinates allowed for the matching of the ACLED to households in the TZNPS.

5.1.5 Socioeconomic and Demographic Information

The TZNPS contains extensive information on socioeconomic and demographic characteristics of individuals and their households. In our analysis, we utilised information on age, gender, maximum educational attainment (no schooling to high school or above), occupational status (not in employment, employed in agriculture, employed in a non-agricultural industry, or family worker), and marital status (monogamous marriage, polygamous marriage, living with partner, divorced/separated, widowed, or never married). We also considered information pertaining to satisfaction with domains of health, financial situation, and housing, measured in the same manner as life satisfaction. Finally, we used information from individuals who reported an overnight stay at a hospital or traditional healer in the past 12 months to capture recent health issues.

At the household level, the TZNPS provided aggregated annual household consumption per adult equivalent in waves 2 and 3, which we adjusted to 2013 prices and took the natural logarithm of to adjust for skewness. We further excluded the 1% tails of the distribution to remove outliers.

Household wealth was captured through three 'asset' indices: a 'household asset index' which totals the number of durable household goods owned; an 'animal asset index' which totals the number of animals owned; and an 'agricultural asset index' which totals the number of agricultural implements owned. We also examined whether the household had borrowed money in the past year. Occupational diversity within the household was also calculated, with this reflecting the total number of different categories of paid employment held by individuals in the household. Further, households were asked to indicate if they received some assistance, be it financial or food-related, from either the government or a non-governmental organisation (NGO) in the past year. Finally, we used information relating to the household's living conditions are included, reflecting if the household has access to a toilet, and if they have access to electricity.

Thus, many factors identified in the literature review as potential determinants of SWB were available in the TZNPS.

5.2 The Armed Conflict Location and Event Data Project

The ACLED Project is a publicly available dataset which provides information on conflict events in numerous countries. Information is provided on the exact date of the event, the event type (battles, explosions/remote violence, protests, riots, strategic developments, and violence against civilians), and the precise location of the events using latitude and longitude coordinates. This information is available annually from 1997, with this study using the data for years 2009 to 2013. The location information from the ACLED data was utilised in conjunction with the TZNPS to construct the conflict intensity index (CII) using the methodology of Bozzoli *et al.* (2011).

Specifically, to construct the CCI, information on the exact location of each conflict event (c_j) from the ACLED and of household *h* from the TZNPS was utilised. We assumed for a given year there are *J* conflict events ordered such that $j = 1, \ldots, J$. The squared distance (*d*) in degrees between each event and household was then estimated, *i.e.*, $d(c_j, h) = \| c_j - h \|^2$. The resulting CII for a household *h* in a given year was given by $\sum_{j=1}^{J} e^{-\alpha(d(c_j,i))}$, where α is the distance-discount factor, with a larger α decreasing the importance of distance of event. Here, we set $\alpha = 10$ here as in Bozzoli *et al.* (2011).

Thus, the CII captures the number of geographically discounted conflict events for each household. This was calculated for each year from 2009 to 2013. An overview of the total number of events and event types in each year is provided in Table C1 of Appendix 1C. In the analysis, the change in CII between year of interview and year prior to interview was calculated for each household, using either 2010 or 2011 for wave 2, and 2012 or 2013 for wave 3.

5.3 Descriptive Statistics

Our baseline estimation sample consisted of an unbalanced panel of 17,461 observations across the 2010/11 and 2012/13 waves of the TZNPS. Table 5.1 provides detailed descriptive statistics for this sample utilised in the baseline analysis.

Mean life satisfaction score in the sample was 3.609, indicating that the average individual in the sample had a satisfaction level falling between "Somewhat dissatisfied" and "Neither satisfied nor dissatisfied". Examining each satisfaction level, the modal response was "Dissatisfied", with 28.5% of the sample reporting this. The next most prevalent response was "Somewhat satisfied" with 22.0% of the sample reporting this, followed by 18.8% of the sample reporting "Satisfied", and 17.5% of the sample reporting "Very dissatisfied". Much lower proportions of the sample reported "Somewhat dissatisfied" and "Very satisfied" (5.4% for both), whilst the least frequent response was "Neither satisfied nor dissatisfied" with only 2.4% of the sample reporting this response.

The most prevalent household shock was 'Large rise in the price of food', with 30.0% of households reporting this. This is not surprising, given that Tanzania experienced significant food price inflation between 2010 and 2013 (Adam *et al.*, 2017). The next most prevalent shock was 'Death of other member of family', with 20.4% of households in the sample reporting this. Prevalence of the other seven shocks was much lower, with 'Death of household member' being the next most prevalent at 5.9% and all the other shocks being reported by under 5% of households.

In our sample, 29.1% of respondents reported being food insecure in the past year, whilst the mean food to total expenditure ratio was 73.1%. Thus, given that a ratio of 65% or higher is generally accepted as indicative of a high risk of food insecurity (Smith and Subandoro, 2007), the average individual within our sample was likely to be highly at risk of food insecurity.

The mean CII score was 1.200, with a minimum of 0, and maximum of 19.841. The mean change in CII was 0.242, indicating on average only small increases in CII were observed in the sample. The minimum change in CII observed was -8.469, whilst the maximum change observed is 13.989, with this value being approximately 11.66 times greater than the mean CII value, and approximately 57.81 times larger than the mean change observed in the sample. Table C1 in Appendix 1C indicates there were very few events in 2009 and 2010 (9 and 5 respectively), before significantly increasing in 2011, 2012, and 2013 (49, 91, and 74 respectively). Most recorded events were protests or riots, or incidences of violence against civilians. Comparatively, very few battles or explosions were recorded. Thus, within the study period the recorded conflict events tended to be less serious in nature.

Examining the individual-level socioeconomic and demographic characteristics of the sample, the mean age was 38.499, whilst 43.6% of the sample were male. Most individuals had primary school education as their highest educational attainment (60.6%), and most were monogamously married (44.5%). As expected, agriculture, livestock, and fishery were the most prevalent industries of work with 57.7% employed in these sectors, followed by employment in a non-agricultural sector (26.2%). Only 6.4% of the sample were not in work at all (either unemployed, unable to work, or a student). Approximately 8.7% of individuals had an overnight stay in a healthcare facility in the last year. For the other three satisfaction domains, we observed both mean health satisfaction (5.408) and mean housing satisfaction (4.405) were higher than mean life satisfaction (3.609) in the sample, suggesting on average individuals were more satisfied with their health and housing than with their life overall. Contrastingly, mean financial satisfaction was lower than mean life satisfaction at 3.080.

Turning to the household-level characteristics, the mean household size for the sample was 6.339, which in adult equivalent terms was 5.152. The mean total annual household consumption was 4,224,546 Tanzanian Shillings (TSh), approximately equal to £1,690 in 2013 (the last year of the survey). In per adult equivalent terms the mean was 934,443 TSh, or approximately £374 in 2013 prices. The mean number of household assets owned was 72.062, whilst the mean number of animals and agricultural implements owned were 13.222 and 3.091 respectively. Approximately 10.8% of households reported they had borrowed cash, goods, or services from someone outside the household or an institution in the past year, whilst 20.9% reported receiving assistance from an NGO or the government in the past year. The mean occupation diversity in the household is 1.093, indicating on average, households generally contained members who all work in the same sector of paid employment. In terms of household facilities, 87.9% had access to a sanitary toilet, whilst 22.5% of households used electricity for lighting. Finally, 57.3% of the sample lived in rural areas, 15.5% in Dar es Salaam, 15.0% in other urban areas, and 12.2% in Zanzibar.

As a preliminary analysis, Table 5.2 provides a comparison of the mean life satisfaction scores for those unaffected and affected by each of the nine household shocks, and those who did and did not report food insecurity in the last 12 months. For all shocks, the mean life satisfaction score was higher for those from household's who were unaffected by the shock compared to those who experienced the shock, with this difference statistically significant for all but 'Death of a household member.' The largest difference of 0.593 points was found for 'Chronic or severe illness or accident of household member.' As per expectations, there was a significant difference in the mean life satisfaction scores by household food insecurity status, with mean life satisfaction scores being 0.500 points higher for those from food secure households compared to those from food insecure

households. This provides preliminary evidence for our first hypothesis that household shocks and food insecurity were negatively associated with life satisfaction.

6. Baseline Specification and Estimation Methodology

This section first presents the baseline specification conducted to test *H1*, followed by an overview of the econometric methods utilised to estimate the specified equation. Subsequently, we present the specification for the robustness test of the results of *H1,* followed by an overview of the methods utilised for the further analyses tested our second and third hypotheses.

6.1 Baseline Specification

Equation (1) presents the baseline specification for the determinants of life satisfaction.

Equation (1)

$$LS_{it}^{*} = \beta_1 S_{it} + \beta_2 FTTER_{it} + \beta_3 FI_{it} + \beta_4 \Delta CII_{it} + \beta_5 X_{it} + \nu_r + \nu_t + \mu_i + \varepsilon_{it}$$

Where *i* indexes individuals, *t* indexes the wave, LS_{it}^{*} is life satisfaction, S_{it} is a vector of shock variables as specified in Table 5.1, $FTTER_{it}$ is this food to total expenditure ratio of the household, FI_{it} is the self-reported food insecurity dummy, ΔCII_{it} is the change in conflict intensity index (CII) between year prior to interview and year of interview, X_{it} is a vector of socioeconomic and demographic control variables, υ_r and υ_t are the regional- and time-specific fixed effects, μ_i is the time-invariant individual-specific random error component, and ε_{it} is the time-varying individual error component. As per *H1,* the expected directions of the coefficients on the shock variables contained in the vector S_{it} were negative, as was the expected direction of the coefficients β_2, β_3, and β_4 on $FTTER_{it}$, FI_{it}, and ΔCII_{it}. The expected coefficients on the controls contained in the vector X_{it} are presented in Table B1 in Appendix 1B, with these expectations based upon findings within the literature. The inclusion of these controls allowed us to assess whether traditional socioeconomic determinants of SWB influenced life satisfaction in our sample over and above the estimated relationships between shocks, conflict, and food insecurity.

6.2 Estimation Methodology

Two methods for estimating *Equation (1)* were utilised, with these methods depending on assumptions made about the outcome variable LS_{it}^{*}. The primary estimation method respected the ordinal nature of the life satisfaction variable by utilising the ordered Probit estimator. The advantage of utilising an ordered Probit model is that it allowed for the calculation of the average marginal effects (AMEs) of the regressors for each of the seven life satisfaction responses. These AMEs indicated the change the probability of an individual reporting a given life satisfaction response associated with each regressor. The drawback of this method was that due to the incidental parameters problem (Greene, 2004) the use of a fixed effects estimator to fully control for time invariant unobserved heterogeneity was precluded. However, to partially negate this issue,

Mundlak-style corrections were employed whereby *Equation (1)* was augmented to include the means of all time-varying regressors for each individual (including all self-reported shocks, the food-to-total expenditure ratio, self-reported food insecurity, change in conflict intensity, household consumption, age, education level, marital status, occupation, household borrowing, household assets, healthcare utilisation, health satisfaction, financial satisfaction, housing satisfaction, household toilet facilities, and household electricity access), with the random effects ordered Probit estimator then utilised. This has been shown to significantly decrease bias from unobserved heterogeneity, with the estimator closely approximating fixed effects (Wooldridge, 2019).

Equation (2) shows the augmented model estimated, with the means of the household shocks represented by the vector $\bar{S}_i$, the mean food to total expenditure ratio by $\overline{FTTER_i}$, the mean self-reported food insecurity by $\overline{FI_i}$, the mean change in CII by $\Delta\overline{CII_i}$, and the mean of the time-varying controls in the vector X_{it} represented by the vector $\bar{Z}_i$.

Equation (2)

$$LS_{it}^{*} = \beta_1 S_{it} + \beta_2 FTTER_{it} + \beta_3 FI_{it} + \beta_4 \Delta CII_{it} + \beta_5 X_{it} + \beta_6 \bar{S}_i + \beta_7 \overline{FTTER_i} + \beta_8 \overline{FI_i} + \beta_9 \Delta\overline{CII_i} + \beta_{10} \bar{Z}_i + \nu_r + \nu_t + \varepsilon_{it}$$

Although offering an improvement on the standard random effects ordered Probit estimator, the model does not fully control for unobserved time-invariant heterogeneity. Thus, we re-estimated *Equation (1)* treating life satisfaction as a continuous variable and using linear fixed effects estimation. The drawback of this method is the interpretation of the estimated coefficients was limited to representing a change in life satisfaction score. All data analyses were conducted utilising Stata 16 (StataCorp, 2019).

6.3 Further Analyses

To test *H2a*, which postulated that food insecurity would moderate the associations between shocks, conflict, and life satisfaction, we interacted each of the shock variables and the conflict variable with the dummy variable for self-reported food insecurity. To test *H2b*, which postulated that consumption quartiles would positively moderate the relationships between shocks and conflict on life satisfaction, whilst residing in the highest consumption quartile would exacerbate the relationship between food insecurity and life satisfaction, we interacted the shock variables, change in CII, and both self-reported food insecurity and risk of food insecurity with a binary variable equal to one if the individual resided in a household from the upper consumption quartile in the sample. To test *H2c*, which postulated that receipt of assistance from the government or an

NGO would provide a protective mechanism against the negative associations between shocks, change in CII, and food insecurity with life satisfaction, we interacted each of these variables with an indicator capturing receipt of such assistance. For both ease of interpretation and robustness against time-invariant heterogeneity, all three models were estimated using the linear fixed effects estimator.

We subsequently explored the potential channels through which the shock variables and conflict may influence life satisfaction. In *H3a* and *H3b*, we respectively hypothesised that food insecurity and consumption would be significant mediators of these relationships. To test this, mediator analysis was conducted using structural equation models (SEM).

SEMs are defined into two parts, the structural part connecting the constructs to one another, and the measurement part connecting the observed variables to the latent variables (Kumar and Upadhaya, 2017). The following assumptions are required for SEM: i) multivariate normality; ii) no systematic missing data; iii) sufficiently large sample size; and iv) correct model specification (Kaplan, 2000). Failure of the normality assumption should not affect the parameter estimates, however standard errors tend to be underestimated. Note that unlike SEM, generalised structural equation modelling (GSEM) does not require this normality assumption (Bagheri and Saadati, 2021). No systematic missing data means that missingness should be missing completely at random (MCAR); however, if there is systematic missingness conditional on observed characteristics, i.e., missing at random (MAR), then multiple imputation methods can be utilised with SEM. Failure to correct for MAR data may lead to biased parameter estimates. Regarding model specification, SEM assumes that the system of equations defined by the structural model does not omit any relevant variables. Omission of relevant variables can lead to substantial parameter estimate bias. Larger samples can reduce specification errors by increasing sample variability, whilst sample size also interacts with the size and type of the specification error (Kaplan 2000).

To allow for the relaxation of the normality assumption, we chose to utilise GSEM for this analysis. We estimated a structural equation whereby the mediator (food insecurity or household consumption) was first regressed on each of the household shocks and change in CII, as well as the covariate controls utilised in the life satisfaction regression. Inclusion of this extensive set of controls helps to reduce potential model misspecification. The estimated coefficients on the shocks and change in CII in the structural model were then multiplied by the estimated coefficient of the mediator variable in the life satisfaction regression to give the indirect effect of the independent variables on life satisfaction through their relationship with the mediator variable. The total effect was then obtained by combining the direct and indirect effects. For both of the

indirect and total effect, we utilised the *nlcom* command in Stata 16 in order for standard errors to be estimated.

We employed the linear GSEM with fixed effects for this analysis. Unfortunately, Stata does not explicitly allow for fixed effects to be included with the *gsem* command. Thus, the data were first transformed using the *xtdata*[1] command to convert them into a suitable format for fixed effects estimation. The estimated coefficients obtained were the same as when the fixed effects estimator was used on the unconverted data. However, as this method makes no adjustment to the estimated covariance matrix for the estimation of the individual means, estimated standard errors will always be too small. Thus, the statistical significance of the coefficients will be overestimated and can only be loosely interpreted.

However, we can approximately adjust for the incorrectly estimated standard errors by multiplying them by a factor correcting for the degrees of freedom, given by the following formula (Bontempi and Golinelli, 2006):

Equation (3)

$$Correct\ SE = \sqrt{\left(\frac{\left(\widehat{SE}\right)^2 * NT}{NT - N - K}\right)}$$

Where $\left(\widehat{SE}\right)^2$ is the square of the incorrectly estimated standard error, NT is the total number of observations, N is the number of individuals, and K is the number of estimated parameters (Bontempi and Golinelli, 2006). In our case, NT equals 17,461, N equals 11,227, and K equals 81 for the life satisfaction model, NT equals 17,470, N equals 11,231, and K equals 70 for the structural model for food insecurity, and NT equals 17,475, N equals 11,234, and Kequals 69 for the structural model for consumption. Note these small differences in N and NT are due to differences in missing observations between the variables included in the models, whilst the structural equations estimate fewer parameters than the life satisfaction model as each shock is entered separately. The same formula can then be utilised to adjust for the estimated standard errors obtained for the indirect and total effects of the shocks on life satisfaction.

[1] See https://www.stata.com/manuals/xtxtdata.pdf

7. Results

In this section, we present the findings of our analysis. Section 7.1 outlines the results of the baseline analysis, examining the direct relationships between shocks, conflict, food insecurity on the one hand, and life satisfaction on the other using an ordered Probit model with Mundlak-style corrections. Subsequently in Section 7.2 we provide the results of a robustness check using linear regression with fixed effects. Section 7.3 focuses on the outcomes of testing our second set of hypotheses regarding the moderating effects of food insecurity, consumption quartile, and receipt of government or NGO assistance. Finally, Section 7.4 presents the results of testing the role of food insecurity and consumption as mediators in the relationships between shocks and conflict with SWB.

7.1 Life Satisfaction: Ordered Probit Regression

Table 7.1 displays the outcomes of the ordered Probit regression model assessing life satisfaction's relationship with the variables detailed in *Equation (1)* of Section 5.1. Columns 1 to 7 provide the estimated average marginal effects (AMEs) associated with each variable for each of the seven possible life satisfaction responses. The analysis was conducted on a final sample of 17,461 observations, encompassing individuals from waves 2 and 3 of the Tanzanian National Panel Survey (TZNPS).

7.1.1 Household Shocks

H1a posited that the nine self-reported household shocks would have a negative association with life satisfaction, leading individuals to be more likely to report low life satisfaction scores and less likely to report high ones.

Table 7.1 demonstrates that three shock variables exhibited the expected negative relationship with life satisfaction. Notably, 'Chronic or severe illness or accident of a household member' displayed the most pronounced association. Individuals in households affected by this shock were 4.0 percentage points more likely to report a life satisfaction level of 1 ("Very dissatisfied") and 2.1 percentage points more likely to report a level of 2 ("Dissatisfied"). The AME for a life satisfaction level of 3 ("Somewhat dissatisfied") was positive but not statistically significant, while at a score of 4 ("Neither satisfied nor dissatisfied"), a significant negative AME was estimated, although this was of negligible size. Larger, significant negative AMEs were found for the remaining three levels of life satisfaction, with individuals from affected households being 1.4 percentage points, 3.0 percentage points, and 1.6 percentage points less likely to report life satisfaction scores of 5 ("Somewhat satisfied"), 6 ("Satisfied"), and 7 ("Very satisfied"), respectively.

The 'Other idiosyncratic shock', encompassing "Jailed", "Fire", and "Dwelling destroyed or damaged", exhibited the next strongest relationship with life satisfaction, though the AMEs were only statistically significant at the 10% level. These AMEs indicated that this shock category was associated with a 3.0 percentage points and 1.6 percentage points higher probability of reporting life satisfaction scores of 1 and 2, respectively. Conversely, this shock category was associated with 1.1 percentage points, 2.3 percentage points, and 1.2 percentage points lower probabilities of reporting life satisfaction scores of 5, 6, and 7, respectively. Similar to 'Chronic or severe illness or accident of a household member', the AME for a life satisfaction score of 3 was positive but not significant, and at a score of 4, the significant negative coefficient was of negligible size.

The final shock exhibiting the expected negative association with life satisfaction was 'Death of other member of family'. The associated AMEs were roughly one-third of the size of those estimated for 'Chronic or severe accident or illness of a household member'. Individuals from households reporting this shock were 1.2 and 0.6 percentage points more likely to report life satisfaction scores of 1 and 2, respectively, and 0.4, 0.9, and 0.5 percentage points more likely to report scores of 5, 6, and 7, respectively. As with the other two shocks, the AME for a life satisfaction score of 3 was positive but not significant, and for a score of 4, the significant negative coefficient was very small in magnitude.

Given that all the shocks represented negative events, it is intriguing that only three showed the anticipated negative relationship with life satisfaction. To explain this, we first consider previous findings from the existing literature, though it is important to acknowledge that these were limited.

Firstly, the non-significant association between a 'Large rise in the price of food' and life satisfaction contradicts the findings of Alem and Kohlin (2014), who reported a negative association between individual perceptions of the impact of food price inflation and life satisfaction. However, their study employed weaker econometric methods with a small cross-sectional sample from Ethiopia. It is plausible that rises in food prices alone are insufficient to generate significant changes in SWB unless accompanied by direct consequences to households' consumption.

Second, our results show a 'Labour market shock' to have a non-significant negative coefficient (though it is close to being significant at the 10% level). This variable encompasses "Loss of salaried employment or non-payment of salary" and/or "Household business failure". This result is partly consistent with Reyes-Garcia *et al.* (2015), who found that recent unemployment was not significantly associated with life satisfaction in a cross-section of 6,973 rural households from 23 countries across Asia, Africa, and Latin America. Nonetheless, this remains a surprising result.

Third, the negative association between 'Chronic or severe accident or illness of a household member' and life satisfaction is partially similar to the findings of Reyes-Garcia *et al.* (2015), who reported that recent household illness or death had a strongly negative association with life satisfaction. However, an issue with this comparison is that illness and death are combined in their study, whereas we separated them and found 'Death of a household member' was not associated with life satisfaction. This result was particularly surprising since 'Death of another family member' was negatively associated with life satisfaction. While one might expect a death within the household to have a more substantial negative effect on subjective wellbeing, it is conceivable that the death of a family member outside the household could come as a greater shock as within a household, individuals might have more knowledge of each other's health. However, this does not provide a definitive explanation, as deaths within a household can still be sudden and unexpected.

The finding that 'Hijacking, burglary, or assault' was not significantly associated with life satisfaction contrasts with Moller (2005), who found a negative association between being a victim of crime and life satisfaction in a cross-sectional study from South Africa. However, Moller (2005) noted that fear of crime, rather than actual victimisation, was more critical to subjective wellbeing, a finding echoed by Jansen *et al.* (2015), where a higher perceived likelihood of being a crime victim was linked to a higher probability of reporting low life satisfaction. Furthermore, we do not observe the specific crime which was experienced, which may explain why we fail to find a significant association.

Similarly, we found that the 'Break-up of the household' shock was not significantly associated with life satisfaction. This variable likely encompasses events such as divorce or other relationship breakdowns within the household. No reviewed paper directly examined this type of shock, but we can propose some reasons for this result. For instance, individuals involved in these situations may have been unhappy in their relationship for an extended period, and the household breakup may not have come as a surprise to them. The separation may have even been amicable for some, leading to a positive impact on the wellbeing of the parties involved.

The 'Other (unspecified) shock' was also not significantly associated with life satisfaction. Due to the lack of information regarding the specific events included in this category, we cannot provide an extensive commentary. Nevertheless, it is somewhat surprising that we did not find a relationship with life satisfaction, given that the household head considered the event significant enough to report.

Additionally, information from the survey on the dispersion of shocks within the community might shed light on why only some shocks were significantly linked to life satisfaction. Household

heads were asked to report the dispersion of the shocks, with Table 7.2 presenting the distribution of responses to this question. Responses of "Only this household" and "Some other households" were categorised as 'Idiosyncratic', while responses of "Most households in this community" and "All households in this community" were considered 'Covariate'. Six shocks were reported as idiosyncratic by over 90% of households. Notably, these included the three shocks significantly associated with lower life satisfaction. Thus, while the idiosyncrasy of a shock was not the sole determining factor for its negative association with life satisfaction, it may influence the wellbeing impact of a shock. For example, if a shock is more covariate, households may find solace in the fact that they are not the only ones experiencing hardship, potentially leading communities to come together during times of collective suffering.

Lastly, the construction of the shock variables may explain why many were not significantly associated with life satisfaction. Firstly, the shocks were reported solely by the household head, while life satisfaction was measured at the individual level. Different household members may have been heterogeneously affected by a given shock. For example, a labour market shock may have the most substantial impact on the household member who lost their job, and its impact on other household members may depend on who lost their job. If it was the primary breadwinner, the impact on other household members would likely be greater if this led to financial hardships. Similarly, a significant rise in food prices might primarily affect the main food purchaser in the household, with other members potentially unaware of the price increase. In contrast, events like 'Chronic or severe illness or accident of a household member' might impact not only the affected member but also other household members who witness a loved one's suffering. Additionally, the death of a family member outside the household might cause shared grief among household members. For the 'Other idiosyncratic shock' variable encompassing "Jailed", "Fire", and "Dwelling destroyed or damaged", it might also be expected that the latter two of these shocks would be more likely to affect the entire household rather than just one individual. This could partially explain why these three shock variables were significantly associated with life satisfaction.

Secondly, although we limited shocks to those reported within the past two years, there likely remains significant heterogeneity within the sample concerning the timing of the reported shocks. While all shocks may have an immediate negative impact on wellbeing, this impact could diminish by the time of the interview. The extent of this reduction may vary by shock, with some having longer-lasting effects than others. For instance, 'Chronic or severe illness or accident of a household member' implies ongoing illness or long-term health consequences. Similarly, the other two shocks significantly negatively related to life satisfaction, 'Death of another family member',

and 'Other idiosyncratic shock', might also have more prolonged effects compared to 'Hijacking, burglary, or assault' or 'the 'Labour market shock', which could be more temporary events.

7.1.2 Conflict

H1b postulated that an increase in conflict intensity would be associated with poorer SWB. Table 7.1 supports this hypothesis, although the estimated average marginal effects (AMEs) were of modest magnitude. Specifically, a one-unit increase in the change in CII corresponded to a 0.2 and 0.1 percentage point reduction in the probability of reporting life satisfaction scores of 1 and 2, respectively. The turning point of this relationship was estimated to be at a score of 4, although the AME was negligible in magnitude. For scores of 5, 6, and 7, the estimated AMEs indicated that individuals were 0.1, 0.2, and 0.1 percentage points less likely to report these scores, respectively. These results suggest that relatively minor increases in the CII have a detectable but limited impact on individuals' wellbeing. The maximum observed increase in the sample of 13.99 units would be associated with an approximate 2.80 and 1.40 percentage point increase in the probability of reporting the two lowest life satisfaction levels and a 1.40, 2.80, and 1.40 percentage point decrease in the probability of reporting the three highest life satisfaction levels, respectively. This is comparable to the estimated AMEs for the 'Other idiosyncratic shock', indicating that substantial increases in CII could generate a noteworthy impact on an individual's wellbeing.

The small magnitude of the relationship found is not necessarily surprising given the relatively low levels of conflict observed in Tanzania during the study period. Indeed, Table C1 in Appendix 1C indicates that most conflict events involved protests, riots, or violence against civilians. Whilst such events may still cause distress, it is reasonable to assume they would have less of an impact on SWB compared to more serious events such as battles or explosions. This highlights a limitation of the CII, whereby no discount factors for the type of event are currently available to apply when calculating the index.

These findings align somewhat with existing literature. Although no study has employed the CII as a determinant of SWB, Welsch (2008) similarly found a strong negative association between an increase in the number of deaths per capita in 21 countries engaged in civil war conflict in 2000 and happiness. Likewise, Shemyakina and Plagnol (2013) discovered that individuals living in municipalities in Bosnia and Herzegovina with higher casualty rates during the previous civil war exhibited lower levels of life satisfaction. Our results can also be compared to the work of Bozzoli *et al.* (2011), who were the first to derive the CII and found some evidence that its value was associated with poorer expectations about future economic circumstances and general life satisfaction. Thus, our results confirm this finding in the context of current life assessment.

7.1.3 Food Insecurity

Table 7.1 provides supporting evidence for *H1c*, with both measures of food insecurity negatively associated with life satisfaction.

For the self-reported food insecurity variable, the estimated AMEs indicate that an individual from a household reporting food insecurity in the past 12 months was 1.6 and 0.8 percentage points more likely to report life satisfaction scores of 1 and 2, respectively. Conversely, they were 0.6, 1.2, and 0.6 percentage points less likely to report the three highest life satisfaction scores. The magnitude of these estimated AMEs was similar to experiencing a 'Death of another family member' shock. This result is consistent with findings in the literature, although all reviewed empirical studies used multinational cross-sectional data (Frongillo *et al.*, 2017; Elgar *et al.*, 2021; Na *et al.*, 2018; Asfahani *et al.*, 2019). Thus, our study provides new evidence of a link between food insecurity and poorer wellbeing, using nationally representative panel survey data from a single country. A qualitative study by Hadley *et al.* (2012) in Ethiopia may offer insight into why this relationship exists, as it found that food insecurity may directly impact wellbeing through the stress and worry it causes, as well as the fear of being negatively perceived by individuals' children and other members of the community.

The AMEs for the food-to-total expenditure ratio indicates that if a household's food-to-total expenditure ratio were to increase by 10 percentage points, an individual within that household would be 0.45 and 0.23 percentage points more likely to report life satisfaction scores of 1 and 2, respectively. Conversely, they would be 0.16, 0.34, and 0.18 percentage points less likely to report life satisfaction scores of 5, 6, and 7, respectively. This provides novel evidence that the risk of food insecurity may also negatively impact SWB, although the magnitude of this association is relatively small.

7.1.4 Control Variables

Given this study was the first to our knowledge to utilise nationally representative panel data to examine the determinants of life satisfaction in Tanzania, it is pertinent to comment on the results for the control variables presented in Table 7.1 in detail. The coefficients indicate which socioeconomic factors appear to be predictors of SWB after accounting for our main variables of interest (shocks, conflict, and food insecurity).

7.1.4.1 Individual-Level Characteristics

Surprisingly, several individual-level socioeconomic controls failed to exhibit significant associations with life satisfaction, despite previous evidence for them being predictors of SWB in

other LMICs. Firstly, male gender did not exhibit a significant association with life satisfaction. This finding contradicts the results from Mwanyangala *et al.*'s (2010) study involving a small sample of elderly individuals from a Tanzanian town and findings from studies conducted in South Africa (Blaauw and Pretorius, 2013) and Ecuador (Nicola *et al.*, 2018). However, it aligns with Reyes-Garcia *et al.*'s (2015) study covering 23 LMICs across Asia, Africa, and Latin America. Age displayed a significant negative relationship with life satisfaction; however, the quadratic term was not statistically significant, implying the absence of the expected U-shaped relationship between age and SWB. Instead, each additional year of age corresponded to a 0.8 and 0.4 percentage point higher probability of an individual reporting life satisfaction scores of 1 and 2, respectively. Conversely, each increasing year of age was associated with a 0.3, 0.6, and 0.3 percentage point lower probability of reporting scores of 5, 6, and 7.

Against expectations, education was not positively linked to life satisfaction. In fact, individuals with primary-level education were 2.3 and 1.2 percentage points more likely to report life satisfaction scores of 1 and 2, respectively, compared to those with no formal schooling, and 0.8, 1.7, and 0.9 percentage points less likely to report the three highest life satisfaction scores. For those with a high school education or higher, a positive but non-significant relationship with life satisfaction was observed. This contrasts with findings from a study using cross-sectional data from Tanzania and Kenya (Jiao *et al.*, 2019). However, Reyes-Garcia *et al.* (2015) found education did not significantly determine life satisfaction in a multinational sample of LMICs, while Bookwalter and Dalenberg (2004) found education only influenced individuals from the upper two consumption quartiles in South Africa. This suggests uncounted heterogeneity by consumption quartiles might explain our result.

Next, only individuals classified as 'Never married' exhibited significantly lower life satisfaction than monogamously married individuals. Relative to monogamously married individuals, those who had never married were 3.5 and 1.8 percentage points more likely to report being "Very dissatisfied" and "Dissatisfied" with their life. Conversely, they were 1.2, 2.6, and 1.4 percentage points less likely to report being "Somewhat satisfied", "Satisfied", and "Very satisfied". This contradicts existing literature (Alem and Kohlin, 2014; Dowdall *et al.*, 2017), which suggests that separated or divorced individuals or widowed individuals were also significantly less likely to exhibit higher levels of life satisfaction.

No significant variation in life satisfaction by occupational status was observed. We expected each of the employment categories to be positively associated with life satisfaction, with unemployment being negatively linked to wellbeing, as often found in the literature (Moller, 2005; Sarracino, 2010;

Jansen *et al.*, 2015). However, the lack of significance in the relationships may be attributed to the relatively low unemployment rate in our sample, with only 6% of respondents not working, meaning there may be relatively low variation in life satisfaction in our omitted reference group.

Next, given the lack of many health-related variables in the TZNPs, we utilised reporting a stay in a healthcare facility in the last 12 months as a measure of health status. This was a relatively weak measure for health-status, and therefore it is unsurprising that we did not find a significant relationship with life satisfaction. What is surprising is the finding that health satisfaction was not positively associated with life satisfaction. This contradicts findings from Ghana, where health was the second most important domain contributing to overall happiness (Nanor *et al.*, 2021). Nevertheless, Bookwalter and Dalenberg (2004) found, using South African data, that health only significantly influenced the life satisfaction of individuals from the wealthiest consumption quartile, potentially due to greater health awareness within this group. Given that Tanzania is less affluent than South Africa, this could explain our findings.

In contrast, financial and housing satisfaction emerged as the two most important predictors of life satisfaction in our sample. For instance, an individual "Dissatisfied" with their financial situation was 10.8 and 5.7 percentage points less likely to report life satisfaction scores of 1 and 2, respectively, compared to an individual "Very dissatisfied" with their financial situation. Conversely, an individual "Very satisfied" with their financial situation was 46.0 and 24.0 percentage points less likely to report life satisfaction scores of 1 and 2. The corresponding figures for housing satisfaction were approximately half the size. The findings of Bookwalter and Dalenberg (2004) may provide insight into this finding, whereby housing conditions were one of the most important drivers of life satisfaction for the poorest consumption quartile of South Africans.

7.1.4.2 Household-Level Characteristics

At the household level, only three variables emerged as significant predictors of life satisfaction. First among these was household consumption, which displayed the expected positive correlation with life satisfaction, albeit the estimated AMEs were relatively small: a 10-percentage point increase in real household consumption per adult equivalent was associated with a 0.11 percentage point reduction in the likelihood of reporting a life satisfaction score of 1 and a 0.05 percentage point increase in the likelihood of reporting a life satisfaction score of 7. This implies consumption levels were not of primary importance to the wellbeing of individuals in our sample.

More substantial predictors of life satisfaction at the household level were the household's location and whether it received financial or food assistance, either from the government or a non-

governmental organisation (NGO). Concerning location, individuals from households in 'Rest of urban' areas exhibited greater life satisfaction than those in Dar es Salaam. Meanwhile, individuals from rural areas reported higher wellbeing than those in 'Rest of urban', with the highest wellbeing observed in Zanzibar. This aligns with expectations derived from the literature, which has consistently shown that urban living is negatively associated with subjective wellbeing and mental health (Jansen *et al.*, 2015; Kannemeyer, 2016; Dowdall *et al.*, 2017). Regarding government or NGO assistance, individuals from households which received support were 2.9 and 1.5 percentage points less likely to report being "Very dissatisfied" and "Dissatisfied" with their lives, respectively. Conversely, they were 1.0, 2.2, and 1.2 percentage points more likely to report "Somewhat satisfied", "Satisfied", and "Very satisfied". This suggests that receiving financial or food assistance may have a positive impact on the SWB of household members.

Contrary to expectations, household facilities, such as access to toilet facilities and electricity, were not significantly associated with life satisfaction. This is surprising, especially considering the strong positive link observed between housing satisfaction and life satisfaction. Furthermore, Jansen *et al.* (2015) found a robust positive association between life satisfaction and water and sanitation facilities, albeit based on cross-sectional data from South Africa. None of the household assets exhibited significant associations with life satisfaction. Although unexpected, this outcome may be attributed to the rough approximations used for wealth measures, given the significant variation in the value of different 'assets' within each index. Additionally, Bookwalter and Dalenberg (2004) found that wealth was only a significant determinant of life satisfaction for those in the upper consumption quartile in South Africa.

In summary, our findings indicated that financial and housing satisfaction were overwhelmingly the most influential determinants of life satisfaction in our sample. Given that a significant proportion of our sample represented economically vulnerable individuals at risk of financial hardships, this is not surprising. Financial satisfaction might serve as an indicator of reduced economic pressure and diminished stress associated with financial vulnerability. The fact that many traditional socioeconomic determinants of life satisfaction were not statistically significant emphasises the relative importance of the household shocks which were associated with lower life satisfaction, alongside conflict and food insecurity, as predictors of subjective wellbeing in our sample.

7.2 Life Satisfaction: Linear Fixed Effects Regression

Table 7.3 presents the results of the robustness check of the preceding results, whereby life satisfaction was treated as a continuous variable allowing for a linear fixed effects regression to be

estimated to fully control for individual level time-invariant heterogeneity. For the sake of brevity, only the coefficients for the key variables of interest were reported, with the full results presented in Table D1 in Appendix 1D. The results indicate our baseline findings from the ordered Probit model were generally robust, at least in terms of sign and statistical significance of the estimated relationships. However, the magnitude of the estimated relationships generally appeared to be smaller than those obtained in the ordered Probit model.

7.2.1 Household Shocks

Table 7.3 shows that, as with the ordered Probit regression, 'Chronic or severe illness or accident of household member', 'Death of other member of family', and 'Other idiosyncratic shock' were the only three household shocks which exhibit a significant negative relationship with life satisfaction. There were some small differences in the relative size and significance of the estimated relationships.

Firstly, whilst 'Other idiosyncratic shock' had the second largest coefficient in our baseline model, here it exhibited the strongest negative relationship with life satisfaction. The estimated coefficient of -0.598 was also now significant at the 1% rather than the 10% level. This implies that an individual from a household which experienced at least one of "Fire", "Jailed", or "Dwelling destroyed or damaged" exhibited a life satisfaction score which was 0.598 points lower than an otherwise identical individual. The coefficient on 'Chronic or severe illness or accident of household member' indicated this shock was associated with a 0.280-point lower life satisfaction score. This relationship was now significant at the 5% rather than 1% level. Finally, 'Death of other member of family' was associated with a 0.097 points lower life satisfaction score, with this relationship now significant at the 10% rather than 5% level. The relative size of the coefficients on 'Death of other member of family' and 'Chronic or severe illness or accident of household member' were similar in both estimation methods, with the former being approximately one-third smaller than the latter.

7.2.2 Conflict

Turning to conflict, our baseline analysis indicated a small but strongly significant negative relationship between the change in CII and life satisfaction. The results in Table 7.2 confirm this negative relationship was robust to full control of unobserved heterogeneity, however the significance of the estimated coefficient fell from 1% to 10%. The estimated coefficient of -0.013 indicates a one-unit increase in CII was associated with a 0.013-point lower life satisfaction score. Thus, experience of the maximum observed increase in CII of 13.99-units would be associated with an approximate 0.19 lower life satisfaction score. This indicates an increase in CII of

maximum magnitude in the sample would have a slightly lower impact on life satisfaction than experiencing a 'Chronic or severe illness or accident of household member' shock. Thus, our finding of a small but statistically significant negative relationship between change in CII and life satisfaction from our baseline estimation method was robust to full control of time-invariant heterogeneity.

7.2.3 Food Insecurity

Finally, Table 7.3 indicates both food insecurity-related measures continued to exhibit the negative relationship with life satisfaction found with the ordered Probit model. The significance of the estimated coefficients for both variables was lower in the fixed effects model, falling from 5% to 10% for the food to total expenditure ratio, and from 1% to 5% for self-reported food insecurity. The coefficient estimated for self-reported food insecurity indicates individuals from household who experienced a lack of food in the last 12 months exhibited a 0.097-point lower life satisfaction score compared to an otherwise identical individual. The coefficient on the food to total expenditure ratio of -0.323 implies that a 10-percentage point increase in the ratio was associated with a 0.032-point lower life satisfaction score. Again, this provides confirmation that the results obtained through the ordered Probit regression were relatively robust to full control of unobserved time invariant heterogeneity.

7.3 Moderating Analysis

We now present the results testing our second set of hypotheses. All models were estimated using linear fixed effects regression for ease of interpretation of the interaction coefficients and full control of unobserved time invariant heterogeneity. As such, we compare the findings to those presented in Table 7.3 for the equivalent fixed effects regression without interaction terms.

7.3.1 Moderation by Food Insecurity Status

H2a proposed that self-reported food insecurity would accentuate the negative associations between the household shocks and conflict with SWB. The results testing this are presented in Table 7.4. These firstly indicate that food insecurity was only a significant moderator for the 'Labour market shock'. This was not found to be associated with life satisfaction in the baseline model. Thus, this result suggests that a labour market shock (job loss or business failure) may only have negative consequences on the SWB of individuals from households that have also reported food insecurity within the past year. Logically, this finding can be rationalised by the notion that individuals from households already grappling with feeding their families, when hit by a job loss or business failure, are likely to face even greater financial hardships. This, in turn, could compound the stresses associated with both events.

We now turn to the findings for the three shocks that were significantly negatively associated with life satisfaction in the baseline model. Firstly, for 'Chronic or severe illness or accident of a household member' and 'Other idiosyncratic shock', we find the estimated negative relationship with life satisfaction remained consistent across both food-secure and food-insecure households. For the 'Death of another family member', the estimated coefficient was negative but not statistically significant. Moreover, it was significantly smaller than the coefficient found in the model without interactions (-0.035 versus -0.094). Correspondingly, the coefficient on the interaction term was -0.178 and nearly statistically significant at the 10% level. Therefore, even though the result technically suggests no divergence in the impact of this shock on SWB based on food insecurity status, it tentatively implies that individuals from food-insecure households might be influencing the negative relationship observed in the baseline model.

Overall, the results provide limited evidence for *H2a* concerning the moderating relationship of food insecurity with household shocks, although seven of the nine interaction terms did display negative coefficients. Thus, perhaps with a more extensive panel and a larger sample size, it is plausible that more precise estimates for these relationships could have been attained.

A more definitive outcome emerged concerning heterogeneity in the impact of conflict on SWB, with the results indicating that only individuals from food-insecure households were adversely affected by increasing conflict levels in the past year. The coefficient on the interaction term suggests that a one-unit increase in the CII was associated with a 0.045-point lower life satisfaction score. Consequently, an individual from a food-insecure household who experienced the maximum change in CII observed in the sample, amounting to 13.99 units, would exhibit an approximate 0.63-point lower life satisfaction score. The magnitude of this effect was approximately three and a half times larger than that found in the model without the interaction term. As postulated, this may be due to the stresses and other negative emotions associated with conflict episodes being exacerbated by the suffering already experienced due to food insecurity. However, it is surprising that conflict alone did not induce a negative impact on wellbeing, although again this may reflect that the overall level of conflict observed in Tanzania during this period was relatively low.

7.3.2 Moderation by Consumption Quartile

H2b firstly proposed that for the self-reported shocks, individuals from households in the highest consumption per adult equivalent quartile might have experienced some protection against adverse consequences on SWB due to their greater economic resources, which could absorb potential financial impacts of shocks. We also posited that those from the top consumption quartile might

better cope with financial repercussions from increased conflict events, such as property damage or limited access to amenities. Moreover, they might have better home security or reside in safer neighbourhoods. Additionally, we proposed an accentuating effect for the upper consumption quartile on the relationship between food insecurity and SWB, drawn from the findings of Elgar *et al.* (2021). Table 7.5 displays the results from the model with interaction terms between the upper consumption quartile indicator and shocks, the change in CII, as well as both self-reported and risk of food insecurity variables.

We found no evidence that individuals from the upper household consumption per adult equivalent quartile were shielded from the SWB impacts of household shocks. This might reflect the reality that most households in Tanzania were still relatively poor in absolute terms. For instance, the mean household consumption per adult equivalent for the fourth quartile was 1,909,367 TSH, equivalent to approximately 5,232 TSH per person per day or $3.14 per person per day (in 2013 prices). Therefore, even though they were relatively wealthier within the sample, they still may have had limited capacity to absorb financial shocks.

Notably, we found an unexpected positive and statistically significant interaction term concerning the 'Large rise in the price of food' shock. This implies that only individuals from wealthier households in the sample experienced a negative impact on their wellbeing when food prices increased. Although this may seem counterintuitive, it could reflect that, in a low-income country like Tanzania, many food items may be perceived as luxury goods. Consequently, rising food prices might have forced wealthier households to reduce dietary diversity and opt for cheaper basic food items. This could lead to diminished SWB, as individuals in these households might be less satisfied with their lives when comparing their current situation to a time when they could afford a more diverse range of foods.

Similarly, we found no evidence of a moderating effect for the upper consumption quartile on conflict. Again, this may be attributed to the low levels of conflict intensity observed in the sample and the less serious nature of the conflict events. It is plausible that the proposed protective effect of greater economic resources might only become significant under much higher levels of conflict intensity which would likely cause greater economic repercussions than one-off protests or isolated incidences of violence against civilians.

Finally, in line with *H3b*, we identified a significant negative coefficient on the interaction between self-reported food insecurity and the upper consumption quartile. This suggests that previous findings from the Gallup World Poll, where the association between relative food insecurity and SWB decreased with the prevalence of food insecurity across countries (Elgar *et al.*, 2021), applied

to our within-country context. In our sample, 31.3% of households in the bottom three consumption quartiles reported experiencing food insecurity in the past 12 months, compared to only 23.2% of those in the highest consumption quartile. Consequently, those in the upper consumption quartile who experienced food insecurity may feel more shame and stigma around being unable to provide sufficiently for their family, and also make unfavourable social comparisons to others in their socioeconomic group. Conversely, those in the lower consumption quartiles might be more accustomed to struggling with food provision and could exhibit some form of habituation that protects their SWB. Furthermore, they may feel relatively less shame from being insecure since many other households in their socioeconomic group were in the same situation.

7.3.3 Moderation by Receipt of Assistance

Finally, *H3c* proposed a protective mechanism against the negative associations between shocks, conflict, and food insecurity on SWB for those who received government or NGO assistance in the past year. Approximately 21% of the sample reported receiving such assistance, which could take various forms including free food distribution, participation in work-for-food or cash-for-work programs, participation in input-exchange programs, scholarships or bursaries for children's education, or any other unlisted form of aid in the TZNPS. We hypothesised that this assistance might alleviate the financial and stress-related impacts of shocks, conflict, and food insecurity.

Table 7.6 reveals limited evidence for *H3c* in our analysis. Assistance only showed a significant positive moderating effect for two shocks. Firstly, we observed that the 'Labour market shock' had a significant negative relationship with life satisfaction for those without recent assistance. In contrast, the significant positive coefficient on the interaction term indicated that those who had received assistance were shielded from this impact. This might be explained by the fact that a 'Labour market shock', such as job loss or business failure, is likely to have substantial financial consequences for households, increasing household worries and stress. Logically, any form of assistance, whether in the form of food or financial resources, could alleviate this impact.

Next, we found that, consistent with our baseline analysis, 'Chronic or severe illness or accident of household member', 'Other idiosyncratic shock', and 'Death of another family member' were all significantly negatively associated with life satisfaction. However, assistance was only found to be a significant positive moderator in the case of the latter. This result is somewhat unexpected because 'Death of another family member' might be less likely to have a financial impact compared to 'Chronic or severe illness or accident of household member.' However, it's possible that the household was reliant on this 'other' family member financially, especially if they were an adult

child or parent providing remittances to the family. Nevertheless, without specific information about the identity of this 'other' family member, it's challenging to draw definitive conclusions regarding this finding.

We did not find a moderating relationship between receipt of assistance and the conflict variable, which is unsurprising given the relatively low level of conflict observed in the sample. Moreover, assistance did not appear to provide protection from self-reported food insecurity. This might be since if households were still food insecure despite receiving assistance, they were likely in a dire financial situation. This observation could also reflect a limitation in the data, as we lacked information on whether food insecurity occurred before or after receiving assistance. However, we did find a significant negative coefficient on the food-to-total-expenditure ratio, accompanied by a significant positive coefficient on the interaction term. The interaction term coefficient was larger than that of the variable itself, indicating that the negative relationship between food insecurity risk and SWB did not apply to households that had received assistance in the past year. This could suggest that if a household had a high food-to-total-expenditure ratio but was also receiving some form of food or financial assistance, their risk of food insecurity was lower than it would otherwise be, and therefore they may be less worried about their situation.

7.4 Generalised Structural Equation Modelling: Mediation Analysis

Finally, we present the results from testing our third set of hypotheses, which proposed that food insecurity (*H3a*) and consumption (*H3b*) may be mediating variables in the relationships between shocks, conflict, and SWB. To test these hypotheses, we employed generalised structural equation modelling (GSEM) with fixed effects. The reader is reminded that Stata does not explicitly support the use of the fixed effects estimator with GSEM. Therefore, we transformed the data into a suitable format for fixed effects estimation. While this approach produces coefficients of the same magnitude as those in a true fixed effects model, the estimated standard errors are smaller than their true value. As such, we subsequently adjusted the estimated standard errors using the method outlined in sub-section 6.3. This method increases the size of the standard errors to closely approximate those which would be obtained through true fixed effects estimation. The efficacy of this approach is demonstrated by the life satisfaction model in the GSEMs (column 1 of Table 7.7 and 7.8), whereby the *t*-statistics obtained for each regressor are almost identical to those obtained in the linear fixed effects model shown in Table 7.3. Additionally, when interpreting the results below, we refer to direct, indirect, and total 'effects', but it should be cautioned that the coefficients cannot be taken as representing causation.

7.4.1 Food Insecurity and Life Satisfaction

Our baseline results indicated that three out of the nine self-reported shocks were negatively associated with life satisfaction, whilst food insecurity also exhibited a negative association with life satisfaction. Likewise, we found that a change in CII was significantly linked to lower life satisfaction. Prior literature has found various self-reported shocks and conflict are linked to worse food security outcomes (Akter and Basher, 2014; Alem and Soderbom, 2012; Bene *et al.*, 2012; Dabalen and Paul, 2014). Consequently, it is plausible that food insecurity acted as a mediating variable between the shocks and conflict with SWB.

Table 7.7 presents the results from GSEM testing *H3a*. Column 1 displays the results of the life satisfaction regression, specified identically to the linear fixed effects baseline model. The estimated coefficients in this column are of the same magnitude as those in Table 7.3 and represent the 'direct effect' of the explanatory variables on life satisfaction. Column 2 provides results for the regression of self-reported food insecurity on the nine self-reported shocks and the change in CII. This structural model includes all controls from the life satisfaction regression, with the food-to-total-expenditure ratio reported for brevity.

The coefficients estimated in Columns 1 and 2 were used to calculate the 'indirect' effect of the shock variables and conflict on life satisfaction shown in Column 3. A statistically significant coefficient for the indirect effect suggests that food insecurity status mediated the relationship between the given explanatory variable and life satisfaction. However, it is possible that the direct relationships between these variables and life satisfaction were not statistically significant. Column 4 presents the 'total effect', which represents the sum of the direct and indirect effects.

The results show that five out of the nine self-reported shocks were associated with a higher likelihood of a household reporting food insecurity in the structural model, indicating that food insecurity was a statistically significant mediating variable between these shocks and life satisfaction. However, among these seven shocks, only 'Chronic or severe accident or illness of a household member', 'Death of another family member', and 'Break-up of the household' exhibited a significant direct effect on life satisfaction. Furthermore, only 'Chronic or severe accident or illness of a household member' exhibited a statistically significant indirect effect. This estimated effect on life satisfaction, mediated through its relationship with food insecurity, resulted in a 0.017-point lower life satisfaction score. Consequently, the total effect of this shock was a 0.297-point lower life satisfaction score, with roughly 6% of this 'effect' attributed to the shock's impact on the likelihood of a household reporting food insecurity. No other shocks exhibited a statistically significant indirect effect on life satisfaction.

Regarding conflict, we found no significant relationship between the change in CII variable and food insecurity, resulting in no indirect effect on life satisfaction. This contrasts with evidence from Dabalen and Paul (2014), who found that conflict negatively impacted food security. However, it is worth noting that the authors used data from the Ivory Coast during a period of civil war encompassing much higher levels of conflict than observed in Tanzania.

Overall, these results suggest that converse to *H3a,* food insecurity was generally not an important mediator in the relationship between self-reported shocks and conflict with SWB.

7.4.2 Consumption and Life Satisfaction

Finally, *H3b* proposed household consumption would serve as a significant mediator between shocks and conflict with SWB. Table 7.8 offers preliminary evidence for this, presenting responses from household heads regarding their perceived impact on income and/or assets for each experienced shock. This shows the majority of households experiencing these shocks reported some form of financial impact. For six of the shocks, over 90% of households reported a loss of income and/or assets. This raises the question of whether these self-reported financial impacts led to reductions in consumption and, if so, whether these declines in consumption indirectly affected life satisfaction. Existing literature provides mixed findings on these possibilities, with some studies linking self-reported shocks such as job loss or wage arrears to reduced consumption (Skoufias, 2003; Alem and Soderbom, 2012), while others found no significant association between various self-reported shocks and consumption levels (Harrower and Hoddinott, 2004; Porter, 2012).

Table 7.9 presents the results for formally testing these hypotheses using GSEM, using the same format as the preceding table. The results revealed that only 'Death of a household member' exhibited a statistically significant negative association with household consumption. The death of a household member could have financial implications that reduce the household's spending power, particularly if the deceased was a significant breadwinner. A 'Large rise in the price of food' also exhibited a negative coefficient in the consumption model, which was close to being statistically significant at the 10% level. Given that the average household in our sample allocated nearly three-quarters of their expenditure to food, a rise in food prices would leave little room for increasing food spending, necessitating reductions in non-food consumption. For both shocks, the negative associations with consumption did not translate into a significant negative indirect effect on life satisfaction.

The conflict variable was also not significantly associated with consumption, resulting in no significant indirect effect. This partially aligns with Welsch (2008) who found the direct effect of

conflict on SWB (*e.g.*, suffering and fear) was much greater than the indirect effect from economic impacts.

Therefore, we found no evidence to support *H3b*, as consumption does not seem to play an important mediating role in the relationship between shocks and conflict with SWB. Furthermore, our findings indicate that the majority of shocks were not negatively linked to consumption, despite the majority of households reporting these shocks had a negative impact on their income and/or assets. This suggests that households were able to smooth their consumption in response to many shocks, which aligns with findings from existing literature where households were generally found to smooth consumption following similar self-reported shocks (Porter, 2012; Skoufias, 2003). The literature also suggests that one mechanism for achieving this is through the sale of assets (Skoufias, 2003; Hadley *et al.*, 2012; Bene *et al.*, 2012). This finding is corroborated in Table 7.8, which shows that, across all shocks, the average percentage of households indicating that a shock led to a reduction in assets (either assets alone or both assets and income) was 41.55%.

8. Conclusion

8.1 Summary of Results

This chapter explored the impact of household shocks, conflict, and food insecurity on subjective wellbeing (SWB) in Tanzania using data from the Tanzanian National Panel Survey (TZNPS) spanning 2010/11 to 2012/13, complemented by data from the Armed Conflict Location and Event (ACLED) Project. We applied various econometric models to test three hypotheses.

First, we used an ordered Probit regression with Mundlak-style corrections to estimate life satisfaction as a function of nine self-reported household shocks, two food insecurity measures (self-reported food insecurity in the past year and the food-to-total expenditure ratio), and a conflict measure derived from ACLED data. Surprisingly, only three of the nine self-reported shocks significantly negatively affected life satisfaction. These were 'Chronic or severe illness or accident of household member', 'Other idiosyncratic shock' (including "Jailed", "Fire", and "Dwelling destroyed or damaged"), and 'Death of other member of the family'. Possible explanations as to why only these shocks were found to significantly predict SWB include their idiosyncratic nature and their likely impact on the entire household. The lack of significant relationships between many shocks and SWB may also reflect the shock variable capturing events any time in the past two years. As such, some shocks may have had a temporary impact on SWB which had dissipated by the time of interview. Results for food insecurity and conflict aligned with expectations. Both the risk of food insecurity (proxied by the food-to-total expenditure ratio) and self-reported food insecurity were negatively associated with life satisfaction. However, the effects were relatively small. Increased conflict intensity was also negatively associated with life satisfaction, but the magnitude of the impact was low given the low levels of conflict observed in our sample. These results were generally robust to linear fixed effects estimation to fully control for unobserved time-invariant heterogeneity, albeit the magnitudes of the estimated relationships were smaller than in the ordered Probit model.

We subsequently tested for moderating effects of food insecurity on the shocks and conflict, and for household consumption quintile and receipt of government or NGO assistance on the shocks, conflict, and food insecurity. Converse to expectations, food insecurity only significantly moderated the 'Labour market shock'. However, we found increased conflict had a stronger negative impact on individuals from food-insecure households. Residing in a household in the upper consumption quartile did not protect individuals from the impacts of the shocks significantly associated with lower life satisfaction, nor conflict. However, consistent with expectations, those residing in the upper consumption quartile exhibited a stronger negative

association between food insecurity and SWB. This provided evidence that the relatively higher prevalence of food insecurity within a household's consumption quartile may increase the impact of food insecurity on SWB. This was in accordance with the findings of Elgar *et al.* (2021), who suggested this may reflect food insecure individuals of higher socioeconomic status making unfavourable social comparisons to others in their socioeconomic group. Receipt of assistance was found to reduce the negative association between the 'Labour market shock' and 'Death of other member of the family' shocks with life satisfaction. This may reflect assistance reducing the financial strain caused by the shocks in the household. However, converse to expectations, receipt of assistance did not reduce the associations between conflict and SWB. This may have been due the less serious nature of the conflict events within our sample. Receipt of assistance also did not reduce the association between food insecurity and SWB. It is plausible this was because the financial situation of such households was so dire that, even with assistance, they still experienced food insecurity.

Finally, we examined household food insecurity status and consumption as potential mediators in the relationship between shocks and conflict with life satisfaction using GSEM. However, our findings provided little evidence that these variables acted as mediators, suggesting that for conflict and those shocks negatively associated with SWB, their direct effect was the most important driver.

8.2 Strengths and Limitations

This study has numerous strengths. Firstly, utilising two waves of panel data enabled us to employ more robust econometric techniques than those previously utilised by studies exploring the determinants of SWB in Tanzania and other African countries, a topic that has been notably under researched (Kabote, 2017; Trudell *et al.*, 2021). The ordered Probit estimator with Mundlak-style corrections catered to the ordinal nature of life satisfaction while controlling for significant unobserved time-invariant heterogeneity. Moreover, this enabled the calculation of Average Marginal Effects (AMEs) for the key variables of interest, offering deeper insights into their relationship with life satisfaction. These results were robust to full control of unobserved time-invariant heterogeneity using by the linear fixed effects estimator. To the best of our knowledge, this paper is the first to investigate the impact of multiple self-reported shocks on SWB using these methods, thereby improving on the previous literature which relied on cross-sectional data and explored single shocks or generic shock indicators. Additionally, the Conflict Intensity Index (CII) provided a more precise measurements than previous approaches relying on municipal-level or subjective conflict measures (Shemyakina and Plagnol, 2003; Wills-Herrera *et al.*, 2011). Our study also incorporated two food insecurity measures, including one that provided a novel link between

a household's risk of food insecurity and poorer SWB. Finally, the moderation and mediation analyses enabled for a deeper exploration in the intertwined relationships between shocks, conflict, food insecurity, and SWB. Such analyses had not previously been conducted in the literature.

There were, however, certain limitations to this work. Firstly, we could not utilise the first or fourth waves of the TZNPS due to the absence of food insecurity data in the former, and household consumption in the latter. A longer panel would have been advantageous, increasing statistical power and allowing for more observations of the shocks. Consequently, in some cases we had to combine separate shocks into multi-shock variables. Even with this, the prevalence of most shocks in the sample was relatively low. We were also unable to determine whether a shock was anticipated or genuinely unexpected. Furthermore, whilst we limited the analysis to shocks which occurred up to two years prior to interview, the low prevalence of shocks in the data meant we could not restrict this further. Additionally, shocks were reported at the household level, but SWB at the individual level. Thus, some shocks may have had a greater impact on the wellbeing of some individuals within a household which was not detected.

Second, our self-reported food insecurity measure was also less comprehensive than measures used in other studies, as it only reflected whether the household experienced food scarcity at some point in the past year, lacking information on severity or frequency. Further, while the CII measure conflict represents an improvement over other measures in the literature, it doesn't distinguish between different types of conflict events. This means that a household located near a battle with civilian casualties would have a lower CII than one located the same distance from multiple protests in a given year. As such, future research is required on deriving a method of weighting different conflict events for the calculation of the CII.

Third, although we found statistically significant relationships between conflict, food insecurity, and some of the self-reported shocks and SWB, these were quantitatively small. This may in part reflect a limitation of utilising life satisfaction as the measure of SWB, which has been shown to be less sensitive to short-term fluctuations than measures such as the GHQ-12 (Powdthavee and van der Berg, 2011). If a measure of psychological distress such as the GHQ-12 had been administered in the TZNPS, then we may have obtained more quantitatively meaningful estimates for the impact of shocks and conflict on SWB.

Finally, although we improved on previous studies in the literature by utilising estimation methods to control for individual-level time invariant heterogeneity, we cannot claim the relationships estimated reflect causality. For this, we would require additional information on strictly

exogeneous shocks so that methods such as difference-in-differences estimation could be employed.

8.3 Future Research and Policy Implications

This chapter advanced our understanding of the impact of shocks, food insecurity, and conflict on SWB. However, there remain areas for further exploration. Collecting more individual-level panel surveys in Sub-Saharan Africa would greatly benefit future research. While several Living Standards Measurement Surveys (LSMS) in the region include data on self-reported shocks like those used in this research, only the TZNPS incorporates a measure of SWB. Expanding the surveys in other nations in Sub-Saharan Africa to include SWB would enable research on the impact of shocks, conflict, and food insecurity on SWB across diverse contexts, facilitating cross-country comparisons. Future surveys should also incorporate more robust food insecurity measures, such as the World Bank's FIES, as well as alternative measures of SWB such as the GHQ-12 which are more sensitive to short-term fluctuations than life satisfaction. Additionally, since our findings suggested that several expected SWB determinants were not important to the Tanzanian population above and beyond shocks, conflict, and food insecurity, further investigation is necessary to understand what matters most for individual's wellbeing in this context.

As our estimates were quantitatively small, we should be cautious in drawing concrete policy implications from this study. That said, we found evidence that individuals from households receiving government or NGO assistance were more resilient against certain shocks, including labour market disruptions. Further, given the associations we observed between food insecurity and SWB, policymakers in Sub-Saharan Africa may be wise to prioritise establishing and maintaining robust social safety nets for their populations. Programs like Ethiopia's Productive Safety Net Programme (PSNP) have proven effective in protecting economic wellbeing and food security against various shocks. While Tanzania has a similar program, there's limited evidence on its impact on both SWB and economic wellbeing, warranting further investigation.

Finally, our study provided novel evidence of a negative relationship between increased conflict and SWB in Sub-Saharan Africa. While the observed impact our study was relatively small, this finding is crucial given the rising threat of conflict in Tanzania. This threat stems from external pressures such as the growing extremism threat in neighbouring Mozambique (Mangena and Pherudi, 2019; AP News, 2020; Walwa, 2022) and internal factors like climate change-related resource depletion and migration (Blocher and Kileli, 2020; Bergius *et al.*, 2020). This highlights

the pressing need for governments worldwide to address climate change to prevent significant resource-driven conflicts arising.

Chapter Two: Tables and Figures

Table 5.1 Descriptive Statistics

Variable	Observations	Mean	S.D.	Min	Max
Dependent Variable					
Life Satisfaction	17,461	3.609	2.018	1	7
Life Satisfaction: "Very Dissatisfied"	17,461	0.175	0.380	0	1
Life Satisfaction: "Dissatisfied"	17,461	0.285	0.451	0	1
Life Satisfaction: "Somewhat Dissatisfied"	17,461	0.054	0.227	0	1
Life Satisfaction: "Neither Satisfied nor Dissatisfied"	17,461	0.024	0.153	0	1
Life Satisfaction: "Somewhat Satisfied"	17,461	0.220	0.414	0	1
Life Satisfaction: "Satisfied"	17,461	0.188	0.391	0	1
Life Satisfaction: "Very Satisfied"	17,461	0.054	0.225	0	1
Household Shock Variables					
Large Rise in the Price of Food	17,461	0.300	0.458	0	1
Labour Market Shock	17,461	0.028	0.166	0	1
Chronic or Severe Illness of Accident of Household Member	17,461	0.030	0.170	0	1
Death of Household Member	17,461	0.059	0.235	0	1
Death of Other Member of Family	17,461	0.204	0.403	0	1
Hijacking, Burglary or Assault	17,461	0.044	0.206	0	1
Break-Up of Household	17,461	0.044	0.206	0	1

Other Idiosyncratic Shock	17,461	0.015	0.120	0	1
Other Unspecified Shock	17,461	0.016	0.126	0	1
Food Insecurity Variables					
Self-Reported Food Insecurity	17,461	0.291	0.454	0	1
Food to Total Expenditure Ratio	17,461	0.731	0.150	0.117	1
Conflict Variables					
Conflict Intensity Index	17,461	1.200	2.971	0	19.841
Change in Conflict Intensity Index	17,461	0.242	2.478	-8.469	13.989
Control Variables					
Age	17,461	38.499	16.380	16	108
Age Squared	17,461	1,750.473	1,520.877	256	11,664
Education Level: None (Omitted)	17,461	0.225	0.418	0	1
Education Level: Primary School	17,461	0.606	0.449	0	1
Education Level: High School or Above	17,461	0.169	0.375	0	1
Male	17,461	0.436	0.496	0	1
Marital Status: Monogamously Married (Omitted)	17,461	0.445	0.497	0	1
Marital Status: Polygamously Married	17,461	0.101	0.302	0	1
Marital Status: Lives with Partner	17,461	0.123	0.328	0	1
Marital Status: Separated or Divorced	17,461	0.080	0.271	0	1
Marital Status: Never Married	17,461	0.178	0.382	0	1

Marital Status: Widowed	17,461	0.073	0.260	0	1
Overnight Stay in Healthcare Facility in Last 12 Months	17,461	0.087	0.282	0	1
Health Satisfaction	17,461	5.408	1.736	1	7
Health Satisfaction: "Very Dissatisfied"	17,461	0.037	0.188	0	1
Health Satisfaction: "Dissatisfied"	17,461	0.108	0.310	0	1
Health Satisfaction: "Somewhat Dissatisfied"	17,461	0.032	0.176	0	1
Health Satisfaction: "Neither Satisfied nor Dissatisfied" (Omitted)	17,461	0.015	0.123	0	1
Health Satisfaction: "Somewhat Satisfied"	17,461	0.115	0.319	0	1
Health Satisfaction: "Satisfied"	17,461	0.431	0.495	0	1
Health Satisfaction: "Very Satisfied"	17,461	0.262	0.440	0	1
Financial Situation Satisfaction	17,461	3.080	1.918	1	7
Financial Satisfaction: "Very Dissatisfied"	17,461	0.217	0.412	0	1
Financial Satisfaction: "Dissatisfied"	17,461	0.373	0.484	0	1
Financial Satisfaction: "Somewhat Dissatisfied"	17,461	0.059	0.236	0	1
Financial Satisfaction: "Neither Satisfied nor Dissatisfied" (Omitted)	17,461	0.029	0.168	0	1
Financial Satisfaction: "Somewhat Satisfied"	17,461	0.146	0.353	0	1
Financial Satisfaction: "Satisfied"	17,461	0.142	0.349	0	1
Financial Satisfaction: "Very Satisfied"	17,461	0.035	0.183	0	1
Housing Satisfaction	17,461	4.405	2.021	1	7
Housing Satisfaction: "Very Dissatisfied"	17,461	0.091	0.287	0	1

Housing Satisfaction: "Dissatisfied"	17,461	0.227	0.419	0	1
Housing Satisfaction: "Somewhat Dissatisfied"	17,461	0.039	0.194	0	1
Housing Satisfaction: "Neither Satisfied nor Dissatisfied" (Omitted)	17,461	0.021	0.143	0	1
Housing Satisfaction: "Somewhat Satisfied"	17,461	0.179	0.384	0	1
Housing Satisfaction: "Satisfied"	17,461	0.336	0.472	0	1
Housing Satisfaction: "Very Satisfied"	17,461	0.107	0.301	0	1
Occupational Status: Unemployed (Omitted)	17,461	0.060	0.237	0	1
Occupational Status: Employed in Agriculture, Livestock, or Fishery	17,461	0.577	0.494	0	1
Occupational Status: Family Employment	17,461	0.097	0.297	0	1
Occupational Status: Employed in a Non-Agricultural Sector	17,461	0.262	0.439	0	1
Occupational Status: Student	17,461	0.004	0.062	0	1
Real Total Household Consumption (TSH)	17,461	4,224,546	4,142,718	120,609	57,500,000
Real Total Household Consumption Per Adult Equivalent	17,461	934,443	815,704	43,480	14,000,000
Log of Real Total Household Consumption Per Adult Equivalent	17,461	13.489	0.698	10.680	16.453
Household Size	14,461	6.339	4.292	1	55
Household Size Adult Equivalents	17,461	5.152	3.386	0.72	42.16
Household Occupational Diversity	17,461	1.093	0.678	0	4
Borrowed in Last 12 Months	17,461	0.107	0.310	0	1
Received Assistance from the Gov't or NGO in Last 12 Months	17,461	0.209	0.406	0	1
Household Asset Index	17,461	72.062	65.705	0	1,144

Animal Asset Index	17,461	13.222	34.463	0	869
Agricultural Asset Index	17,461	3.091	3.517	0	34
Access to Toilet Facilities	17,461	0.879	0.362	0	1
Household has Electricity	17,461	0.225	0.417	0	1
Area: Dar es Salaam (Omitted)	17,461	0.155	0.362	0	1
Area: Other Urban	17,461	0.150	0.358	0	1
Area: Rural	17,461	0.573	0.495	0	1
Area: Zanzibar	17,461	0.122	0.327	0	1
Balanced Panel	17,461	0.859	0.349	0	1
Notes: Figures correct to three decimal places for binary variables.					

Table 5.2 Comparison of Mean Life Satisfaction by Household Shocks and Food Insecurity Status

Variable	Mean Life Satisfaction (=0)	Mean Life Satisfaction (=1)	Difference (S.E)	t-statistic
Large Rise in the Price of Food	3.673	3.462	0.211*** (0.033)	6.33
Labour Market Shock	3.618	3.309	0.309*** (0.092)	3.36
Chronic or Severe Illness or Accident of Household Member	3.627	3.034	0.593*** (0.089)	6.63
Death of Household Member	3.612	3.574	0.038 (0.065)	0.58
Death of Other Member of Family	3.674	3.357	0.318*** (0.038)	8.40
Hijacking, Burglary or Assault	3.629	3.398	0.221*** (0.074)	2.98
Break-Up of Household	3.618	3.393	0.225*** (0.080)	2.82
Other Idiosyncratic Shock	3.613	3.359	0.254** (0.127)	2.00
Other Unspecified Shock	3.618	3.107	0.511*** (0.122)	4.20
Food Insecure	3.755	3.255	0.500*** (0.033)	14.96

Notes: Statistics based on primary sample used in the regression analyses (N=17,461). Figures are correct to three decimal places. Statistical significance of difference in means is indicated by *** at the 1% level, ** at the 5% level, and * at the 10% level.

Table 7.1 Life Satisfaction: Ordered Probit Regression

Variable	(1) AME: LS = 1 (z-stat)	(2) AME: LS = 2 (z-stat)	(3) AME: LS = 3 (z-stat)	(4) AME: LS = 4 (z-stat)	(5) AME: LS = 5 (z-stat)	(6) AME: LS = 6 (z-stat)	(7) AME: LS = 7 (z-stat)
Large Rise in the Price of Food	0.006 (1.14)	0.003 (1.14)	0.000 (0.91)	-0.000 (-1.13)	-0.002 (-1.14)	-0.004 (-1.14)	-0.002 (-1.14)
Labour Market Shock	0.022 (1.61)	0.012 (1.61)	0.000 (1.11)	-0.000 (-1.59)	-0.008 (-1.61)	-0.017 (-1.61)	-0.009 (-1.61)
Chronic or Severe Illness or Accident of Household Member	0.040*** (3.16)	0.021*** (3.16)	0.000 (1.38)	-0.000*** (-2.97)	-0.014*** (-3.16)	-0.030*** (-3.16)	-0.016*** (-3.16)
Death of Household Member	-0.009 (-0.97)	-0.005 (-0.97)	-0.000 (-0.82)	0.000 (0.96)	0.003 (0.97)	0.007 (0.97)	0.004 (0.97)
Death of Other Member of Family	0.012** (2.12)	0.006** (2.12)	0.000 (1.25)	-0.000** (-2.06)	-0.004** (-2.12)	-0.009** (-2.12)	-0.005** (-2.12)
Hijacking, Burglary or Assault	-0.008 (-0.73)	-0.004 (-0.73)	-0.000 (-0.66)	0.000 (0.72)	0.003 (0.73)	0.006 (0.73)	0.003 (0.73)
Break-Up of Household	0.013 (0.98)	0.007 (0.98)	0.000 (0.83)	-0.000 (-0.98)	-0.005 (-0.98)	-0.010 (-0.98)	-0.005 (-0.98)
Other Idiosyncratic Shock	0.030* (1.65)	0.016* (1.65)	0.000 (1.12)	-0.000* (-1.65)	-0.011* (-1.65)	-0.023* (-1.65)	-0.012* (-1.65)
Other Unspecified Shock	0.009 (0.46)	0.005 (0.46)	0.000 (0.44)	-0.000 (-0.46)	-0.003 (-0.46)	-0.007 (-0.46)	-0.004 (-0.46)
Change in Conflict Intensity Index	0.002*** (2.59)	0.001*** (2.59)	0.000 (1.32)	-0.000** (-2.49)	-0.001*** (-2.59)	-0.002*** (-2.59)	-0.001*** (-2.59)
Log of Real Household Consumption	-0.011** (-2.04)	-0.006** (-2.04)	-0.000 (-1.23)	0.000** (1.99)	0.004** (2.04)	0.008** (2.04)	0.005** (2.04)

Food to Total Expenditure Ratio	0.045** (2.25)	0.023** (2.25)	0.000 (1.27)	-0.000** (-2.18)	-0.016** (-2.25)	-0.034** (-2.25)	-0.018** (-2.25)
Food Insecure	0.016*** (2.56)	0.008*** (2.56)	0.000 (1.32)	-0.000** (-2.46)	-0.006*** (-2.56)	-0.012*** (-2.56)	-0.006*** (-2.56)
Male	0.006 (1.47)	0.003 (1.47)	0.000 (1.06)	-0.000 (-1.45)	-0.002 (-1.47)	-0.004 (-1.47)	-0.002 (-1.47)
Age	0.008* (1.76)	0.004* (1.76)	0.000 (1.16)	-0.000* (-1.72)	-0.003* (-1.76)	-0.006* (-1.76)	-0.003 (-1.76)
Age Squared	-0.000 (-0.73)	-0.000 (-0.73)	-0.000 (-0.45)	0.000 (0.66)	0.000 (0.73)	0.000 (0.73)	0.000 (0.73)
Education Level: Primary School	0.023* (1.86)	0.012 (1.86)	0.000 (1.19)	-0.000* (-1.82)	-0.008* (-1.86)	-0.017* (-1.86)	-0.009 (-1.86)
Education Level: High School or Above	-0.012 (-0.56)	-0.006 (-0.56)	-0.000 (-0.52)	0.000 (0.55)	0.004 (0.56)	0.009 (0.56)	0.005 (0.56)
Marital Status: Polygamously Married	-0.014 (-1.11)	-0.007 (-1.11)	-0.000 (-0.90)	0.000 (1.10)	0.005 (1.11)	0.010 (1.11)	0.006 (1.11)
Marital Status: Lives with Partner	0.007 (0.76)	0.003 (0.76)	0.000 (0.68)	-0.000 (-0.76)	-0.002 (-0.76)	-0.005 (-0.76)	-0.003 (-0.76)
Marital Status: Separated or Divorced	0.013 (1.00)	0.007 (1.00)	0.000 (0.84)	-0.000 (-0.99)	-0.005 (-1.00)	-0.010 (-1.00)	-0.005 (-0.99)
Marital Status: Never Married	0.035*** (2.67)	0.018*** (2.67)	0.000 (1.33)	-0.000*** (-2.56)	-0.012*** (-2.67)	-0.026*** (-2.67)	-0.014*** (-2.67)
Marital Status: Widow(er)	-0.006 (-0.34)	-0.003 (-0.34)	-0.000 (-0.33)	0.000 (0.34)	0.002 (0.34)	0.004 (0.34)	0.002 (0.34)
Occupational Status: Employed in Agriculture, Livestock, or Fishery	0.012 (0.81)	0.007 (0.81)	0.000 (0.72)	-0.000 (-0.81)	-0.004 (-0.81)	-0.009 (-0.81)	-0.005 (-0.81)

Occupation Status: Family Employment	-0.001 (-0.07)	-0.001 (-0.07)	-0.000 (-0.07)	0.000 (0.07)	0.000 (0.07)	0.001 (0.07)	0.000 (0.07)
Occupational Status: Employed in Non-Agricultural Sector	0.001 (0.05)	0.000 (0.05)	0.000 (0.05)	-0.000 (-0.05)	-0.000 (-0.05)	-0.001 (-0.05)	-0.000 (-0.05)
Occupational Status: Student	0.000 (0.01)	0.000 (0.01)	0.000 (0.01)	-0.000 (-0.01)	-0.000 (-0.01)	-0.000 (-0.01)	-0.000 (-0.01)
Household Occupational Diversity	-0.008 (-1.41)	-0.004 (-1.41)	-0.000 (-1.04)	0.000 (1.39)	0.003 (1.41)	0.006 (1.41)	0.003 (1.41)
Borrowed in Last 12 Months	-0.008 (-1.01)	-0.004 (-1.01)	-0.000 (-0.85)	0.000 (1.00)	0.000 (1.01)	0.006 (1.01)	0.003 (1.01)
Household Asset Index	-0.000 (-0.44)	-0.000 (-0.44)	-0.000 (-0.24)	0.000 (0.41)	0.000 (0.44)	0.000 (0.44)	0.000 (0.44)
Animal Asset Index	-0.000 (-0.73)	-0.000 (-0.73)	-0.000 (-0.60)	0.000 (0.71)	0.000 (0.73)	0.000 (0.73)	0.000 (0.73)
Agricultural Asset index	0.001 (0.90)	0.001 (0.90)	0.000 (0.78)	-0.000 (-0.90)	-0.000 (-0.90)	-0.001 (-0.90)	-0.000 (-0.90)
Overnight Stay in Healthcare Facility in Last 12 Months	0.012 (1.41)	0.006 (1.41)	0.000 (1.04)	-0.000 (-1.39)	-0.004 (-1.41)	-0.009 (-1.41)	-0.005 (-1.41)
Health Satisfaction: "Dissatisfied"	-0.004 (-0.31)	-0.002 (-0.31)	-0.000 (-0.30)	0.000 (0.31)	0.002 (0.31)	0.003 (0.31)	0.002 (0.31)
Health Satisfaction: "Somewhat Dissatisfied"	0.008 (0.43)	0.004 (0.43)	0.000 (0.41)	-0.000 (-0.43)	-0.003 (-0.43)	-0.006 (-0.43)	-0.003 (-0.43)
Health Satisfaction: "Neither Satisfied nor Dissatisfied"	0.014 (0.57)	0.007 (0.57)	0.000 (0.53)	-0.000 (-0.57)	-0.005 (-0.57)	-0.010 (-0.57)	-0.006 (-0.57)
Health Satisfaction: "Somewhat Satisfied"	-0.012 (-0.82)	-0.006 (-0.82)	-0.000 (-0.72)	0.000 (0.81)	0.004 (0.82)	0.009 (0.82)	0.005 (0.82)

Health Satisfaction: "Satisfied"	-0.007 (-0.53)	-0.004 (-0.53)	-0.000 (-0.50)	0.000 (0.53)	0.003 (0.53)	0.005 (0.53)	0.003 (0.53)
Health Satisfaction: "Very Satisfied"	0.019 (1.35)	0.010 (1.35)	0.000 (1.02)	-0.000 (-1.33)	-0.007 (-1.35)	-0.014 (-1.35)	-0.008 (-1.35)
Financial Satisfaction: "Dissatisfied"	-0.108*** (-14.95)	-0.057*** (-14.30)	-0.000 (-1.51)	0.001*** (7.96)	0.038*** (14.71)	0.082*** (14.54)	0.045*** (13.90)
Financial Satisfaction: "Somewhat Dissatisfied"	-0.138*** (-12.32)	-0.072*** (-12.01)	-0.000 (-1.51)	0.001*** (7.36)	0.048*** (12.20)	0.104*** (12.14)	0.057*** (11.71)
Financial Satisfaction: "Neither Satisfied nor Dissatisfied"	-0.185*** (-11.55)	-0.097*** (-11.36)	-0.001 (-1.52)	0.002*** (7.14)	0.065*** (11.43)	0.139*** (11.43)	0.076*** (11.09)
Financial Satisfaction: "Somewhat Satisfied"	-0.207*** (-23.22)	-0.108*** (-22.25)	-0.001 (-1.53)	0.002*** (8.31)	0.072*** (22.09)	0.156*** (22.86)	0.086*** (20.10)
Financial Satisfaction: "Satisfied"	-0.276*** (-28.63)	-0.144*** (-27.48)	-0.001 (-1.54)	0.002*** (8.28)	0.097*** (25.43)	0.208*** (28.74)	0.114*** (24.04)
Financial Satisfaction: "Very Satisfied"	-0.460*** (-28.29)	-0.240*** (-26.53)	-0.001 (-1.54)	0.004*** (8.14)	0.161*** (23.45)	0.345*** (27.51)	0.190*** (26.06)
Housing Satisfaction: "Dissatisfied"	-0.050*** (-4.90)	-0.026*** (-4.83)	-0.000 (-1.43)	0.000*** (4.40)	0.018*** (4.87)	0.038*** (4.86)	0.021*** (4.85)
Housing Satisfaction: "Somewhat Dissatisfied"	-0.086*** (-6.00)	-0.045*** (-5.91)	-0.000 (-1.46)	0.001*** (5.08)	0.030*** (5.96)	0.065*** (5.95)	0.035*** (5.91)
Housing Satisfaction: "Neither Satisfied nor Dissatisfied"	-0.054*** (-2.70)	-0.028*** (-2.68)	-0.000 (-1.31)	0.000*** (2.60)	0.019*** (2.69)	0.041*** (2.69)	0.022*** (2.69)
Housing Satisfaction: "Somewhat Satisfied"	-0.097*** (-9.25)	-0.051*** (-8.96)	-0.000 (-1.49)	0.001*** (6.64)	0.034*** (9.12)	0.073*** (9.10)	0.040*** (8.97)
Housing Satisfaction: "Satisfied"	-0.137*** (-13.53)	-0.072*** (-12.95)	-0.000 (-1.51)	0.001*** (7.63)	0.048*** (13.15)	0.103*** (13.23)	0.057*** (12.78)

Housing Satisfaction: "Very Satisfied"	-0.203*** (-16.97)	-0.106*** (-16.15)	-0.001 (-1.52)	0.002*** (7.96)	0.071*** (16.19)	0.153*** (16.50)	0.084*** (15.83)
Received Assistance from the Gov't or NGO in Last 12 Months	-0.029*** (-4.91)	-0.015*** (-4.91)	-0.000 (-1.47)	0.000*** (4.28)	0.010*** (4.89)	0.022*** (4.91)	0.012*** (4.89)
Household Access to Toilet Facilities	-0.015 (-1.53)	-0.008 (-1.53)	-0.000 (-1.09)	0.000 (1.51)	0.005 (1.53)	0.011 (1.53)	0.006 (1.53)
Household has Electricity	-0.008 (-0.67)	-0.005 (-0.67)	-0.000 (-0.61)	0.000 (0.67)	0.003 (0.67)	0.006 (0.67)	0.003 (0.67)
Area: Rest of Urban	-0.065 (-4.04)	-0.034 (-4.02)	-0.000 (-1.43)	0.001*** (3.68)	0.023*** (4.02)	0.049*** (4.03)	0.027*** (4.02)
Area: Rural	-0.070 (-4.32)	-0.037 (-4.30)	-0.000 (-1.44)	0.001*** (3.90)	0.025*** (4.30)	0.053*** (4.31)	0.029*** (4.29)
Area: Zanzibar	-0.280 (-3.39)	-0.146 (-3.39)	-0.001 (-1.41)	0.002*** (3.15)	0.098*** (3.38)	0.211*** (3.39)	0.116*** (3.38)
Wave 3	0.009 (1.53)	0.004 (1.53)	0.000 (1.07)	-0.000 (-1.51)	-0.003 (-1.53)	-0.006 (-1.53)	-0.003 (-1.53)
Regional Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	17,461	17,461	17,461	17,461	17,461	17,461	17,461

Notes: Model estimated using linear regression with fixed effects. Additional control variables, including time and region dummies, are included but not reported for brevity. Coefficients are reported to 3 decimal places. T-statistics are reported to 2 decimal places and are in parentheses. Statistical significance indicated by * at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 7.2 Self-Reported Community Dispersion of Household Shocks

Shock	Covariate	Idiosyncratic
Large Rise in the Price of Food	83.07%	16.93%
Labour Market Shock	33.98%	66.02%
Chronic or Severe Illness or Accident of Household Member	2.16%	97.84%
Death of Household Member	3.97%	96.03%
Death of Other Member of Family	9.70%	90.30%
Hijacking, Burglary or Assault	2.63%	97.37%
Break-Up of Household	1.91%	98.09%
Other Idiosyncratic Shock	6.17%	93.93%
Other Unspecified Shock	73.40%	26.60%

Table 7.3 Life Satisfaction: Linear Regression with Fixed Effects

Variable	(1) Coefficient (t-stat)
Large Rise in the Price of Food	-0.028 (-0.60)
Labour Market Shock	-0.048 (-0.38)
Chronic or Severe Illness or Accident of Household Member	-0.280** (-2.36)
Death of Household Member	0.063 (0.72)
Death of Other Member of Family	-0.094* (-1.81)
Hijacking, Burglary or Assault	-0.072 (-0.70)
Break-Up of Household	-0.154 (-1.30)
Other Idiosyncratic Shock	-0.598*** (-3.60)
Other Unspecified Shock	0.087 (0.51)
Change in Conflict Intensity Index (Between Year of Interview and Year Prior to Interview)	-0.013* (-1.78)
Log of Real Household Consumption	0.092* (1.78)
Food to Total Expenditure Ratio	-0.323* (-1.74)
Food Insecure	-0.097** (-1.96)
Individual Controls	Yes
Household Controls	Yes
Time Fixed Effects	Yes
Regional Fixed Effects	Yes
N	17,461

Notes: Model estimated using linear regression with fixed effects. Additional control variables, including time and region dummies, are included but not reported for brevity. Coefficients are reported to 3 decimal places. T-statistics are reported to 2 decimal places and are in parentheses. Statistical significance indicated by * at the 10% level, ** at the 5% level, and *** at the 1% level. Full results provided in Table D1 in Appendix 1D.

Table 7.4 Life Satisfaction: Moderation by Food Insecurity Status

Variable	(1) Coefficient (t-stat)
Large Rise in the Price of Food	0.005 (0.10)
Large Rise in the Price of Food * Food Insecure	-0.112 (-1.16)
Labour Market Shock	0.172 (1.09)
Labour Market Shock * Food Insecure	-0.551** (-2.20)
Chronic or Severe Illness or Accident of Household Member	-0.269* (-1.77)
Chronic or Severe Illness or Accident of Household Member * Food Insecure	-0.033 (-0.14)
Death of Household Member	0.079 (0.78)
Death of Household Member * Food Insecure	-0.051 (-0.27)
Death of Other Member of Family	-0.036 (-0.59)
Death of Other Member of Family * Food Insecure	-0.178 (-1.59)
Hijacking, Burglary or Assault	-0.081 (-0.66)
Hijacking, Burglary or Assault * Food Insecure	0.048 (0.22)
Break-Up of Household	-0.048 (-0.34)
Break-Up of Household * Food Insecure	-0.316 (-1.33)
Other Idiosyncratic Shock	-0.535*** (-2.73)
Other Idiosyncratic Shock * Food Insecure	-0.271 (-0.74)
Other Unspecified Shock	0.016 (0.07)
Other Unspecified Shock * Food Insecure	0.053 (0.15)
Change in Conflict Intensity Index	0.002 (0.23)
Change in Conflict Intensity Index * Food Insecure	-0.045** (-2.54)
Food to Total Expenditure Ratio	-0.335* (-1.81)
Food Insecure	0.005 (0.10)

Individual Controls	Yes
Household Controls	Yes
Time Fixed Effects	Yes
Regional Fixed Effects	Yes
N	17,461

Notes: Model estimated using linear regression with fixed effects. Additional control variables, including time and region dummies, are included but not reported for brevity. Coefficients are reported to 3 decimal places. T-statistics are reported to 2 decimal places and are in parentheses. Statistical significance indicated by * at the 10% level, ** at the 5% level, and *** at the 1% level. Full results available on request.

Table 7.5 Life Satisfaction: Moderation by Consumption Quartile

Variable	(1) Coefficient (t-stat)
Consumption Q4	3.387 (1.58)
Large Rise in the Price of Food	0.022 (0.43)
Large Rise in the Price of Food * Consumption Q4	-0.196* (-1.91)
Labour Market Shock	0.098 (0.57)
Labour Market Shock * Consumption Q4	-0.283 (-1.15)
Chronic or Severe Illness or Accident of Household Member	-0.259* (-1.88)
Chronic or Severe Illness or Accident of Household Member * Consumption Q4	-0.044 (-0.16)
Death of Household Member	0.060 (0.61)
Death of Household Member * Consumption Q4	0.022 (0.10)
Death of Other Member of Family	-0.101* (-1.65)
Death of Other Member of Family * Consumption Q4	0.043 (0.39)
Hijacking, Burglary or Assault	0.011 (0.09)
Hijacking, Burglary or Assault * Consumption Q4	-0.246 (-1.19)
Break-Up of Household	-0.151 (-1.07)
Break-Up of Household * Consumption Q4	-0.026 (-0.10)
Other Idiosyncratic Shock	-0.483*** (-2.50)
Other Idiosyncratic Shock * Consumption Q4	-0.434 (-1.13)
Other Unspecified Shock	0.153 (0.69)
Other Unspecified Shock * Consumption Q4	-0.154 (-0.43)
Change in Conflict Intensity Index	-0.012 (-0.74)
Change in Conflict Intensity Index * Consumption Q4	-0.003 (-0.15)
Food to Total Expenditure Ratio	-0.182 (-0.82)

Food to Total Expenditure Ratio * Consumption Q4	-0.437 (-1.26)
Food Insecure	-0.030 (-0.53)
Food Insecure * Consumption Q4	-0.295*** (-2.69)
Individual Controls	Yes
Household Controls	Yes
Time Fixed Effects	Yes
Regional Fixed Effects	Yes
N	17,461

Notes: Model estimated using linear regression with fixed effects. Additional control variables, including time and region dummies, are included but not reported for brevity. Coefficients are reported to 3 decimal places. T-statistics are reported to 2 decimal places and are in parentheses. Statistical significance indicated by * at the 10% level, ** at the 5% level, and *** at the 1% level. Full results available on request.

Table 7.6 Life Satisfaction: Moderation by Receipt of Government or NGO Assistance

Variable	(1) Coefficient (t-stat)
Large Rise in the Price of Food	-0.001 (-0.01)
Large Rise in the Price of Food * Assistance	-0.094 (-0.87)
Labour Market Shock	-0.226* (-1.84)
Labour Market Shock * Assistance	1.001*** (3.29)
Chronic or Severe Illness or Accident of Household Member	-0.279*** (-2.01)
Chronic or Severe Illness or Accident of Household Member * Assistance	0.053 (0.21)
Death of Household Member	0.113 (1.08)
Death of Household Member * Assistance	-0.190 (-0.98)
Death of Other Member of Family	-0.134** (-2.33)
Death of Other Member of Family * Assistance	0.224* (1.70)
Hijacking, Burglary or Assault	-0.157 (-1.35)
Hijacking, Burglary or Assault * Assistance	0.331 (1.36)
Break-Up of Household	-0.136 (-1.04)
Break-Up of Household * Assistance	-0.172 (-0.62)
Other Idiosyncratic Shock	-0.519*** (-2.66)
Other Idiosyncratic Shock * Assistance	-0.258 (-0.74)
Other Unspecified Shock	0.020 (0.10)
Other Unspecified Shock * Assistance	0.326 (0.82)
Change in Conflict Intensity Index	-0.011 (-1.39)
Change in Conflict Intensity Index * Assistance	-0.030 (-0.79)
Food to Total Expenditure Ratio	-0.474** (-2.37)
Food to Total Expenditure Ratio * Assistance	0.721** (2.05)
Food Insecure	-0.062 (-1.13)
Food Insecure * Assistance	-0.120 (-1.09)
Assistance	-0.342 (-1.23)

Individual Controls	Yes
Household Controls	Yes
Time Fixed Effects	Yes
Regional Fixed Effects	Yes
N	17,461

Notes: Model estimated using linear regression with fixed effects. Additional control variables, including time and region dummies, are included but not reported for brevity. Coefficients are reported to 3 decimal places. T-statistics are reported to 2 decimal places and are in parentheses. Statistical significance indicated by * at the 10% level, ** at the 5% level, and *** at the 1% level. Full results available on request.

Table 7.7 Life Satisfaction and Food Insecurity: Generalised Structural Equation Model

Variable	(1) Life Satisfaction	(2) Food Insecurity	(3) Indirect Effect	(4) Total Effect
	Coefficient (t-stat)	Coefficient (t-stat)	Coefficient (t-stat)	Coefficient (t-stat)
Large Rise in the Price of Food	-0.028 (-0.60)	0.035*** (2.99)	-0.003 (-1.62)	-0.032 (-0.68)
Labour Market Shock	-0.048 (-0.38)	0.087*** (2.71)	-0.008 (-1.16)	-0.056 (-0.33)
Chronic or Severe Illness or Accident of Household Member	-0.280** (-2.36)	0.179*** (5.90)	-0.017* (-1.85)	-0.297** (-2.51)
Death of Household Member	0.063 (0.68)	-0.017 (-0.31)	0.002 (0.72)	0.064 (0.73)
Death of Other Member of Family	-0.094* (-1.74)	0.015 (1.12)	-0.001 (-0.97)	-0.095* (-1.84)
Hijacking, Burglary or Assault	-0.072 (-0.69)	0.047* (1.79)	-0.005 (-1.32)	-0.077 (-0.74)
Break-Up of Household	-0.154 (-1.29)	0.042 (1.38)	-0.004 (-1.12)	-0.158 (-1.32)
Other Idiosyncratic Shock	-0.598*** (-3.60)	-0.067 (-1.58)	0.006 (1.23)	-0.591*** (-3.56)
Other Unspecified Shock	0.087 (0.51)	0.075* (1.71)	-0.007 (1.28)	0.079 (0.46)
Change in Conflict Intensity Index	-0.013* (-1.76)	0.001 (0.38)	-0.000 (-0.38)	-0.013* (-1.79)
Food to Total Expenditure Ratio	-0.323* (-1.74)	0.071 (1.49)	-0.007 (-1.18)	-0.330* (-1.78)
Food Insecure	-0.097** (-1.96)	-	-	-0.097** (-1.96)
Individual Controls	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes

Regional Fixed Effects	Yes	Yes	Yes	Yes
N	17,461	17,470	17,461	17,461

Notes: Model estimated using a linear generalised structural equation model with fixed effects. Additional control variables, including time and region dummies, are included but not reported for brevity. Coefficients are reported to 3 decimal places. T-statistics are reported to 2 decimal places and are in parentheses. Statistical significance indicated by * at the 10% level, ** at the 5% level, and *** at the 1% level. Full results available on request.

Table 7.8 Self-Reported Financial Impact of Household Shocks

Shock	Income Loss	Asset Loss	Loss of Both	Loss of Neither
Large Rise in the Price of Food	73.33%	5.55%	18.92%	2.21%
Labour Market Shock	51.42%	1.94%	46.51%	0.13%
Chronic or Severe Illness or Accident of Household Member	54.22%	4.11%	33.55%	8.12%
Death of Household Member	39.07%	3.91%	26.56%	30.46%
Death of Other Member of Family	36.16%	3.52%	12.32%	48.00%
Hijacking, Burglary or Assault	46.64%	25.95%	23.74%	3.68%
Break-Up of Household	28.63%	10.50%	22.06%	38.81%
Other Idiosyncratic Shock	38.87%	23.32%	33.24%	4.56%
Other Unspecified Shock	17.99%	3.65%	74.58%	3.78%

Table 7.9 Life Satisfaction and Household Consumption Per Adult Equivalent: Generalised Structural Equation Model

Variable	(1) Life Satisfaction	(2) Consumption	(3) Indirect Effect	(4) Total Effect
	Coefficient (t-stat)	Coefficient (t-stat)	Coefficient (t-stat)	Coefficient (t-stat)
Large Rise in the Price of Food	-0.028 (-0.60)	-0.018 (-1.57)	-0.002 (-1.18)	-0.030 (-1.11)
Labour Market Shock	-0.048 (-0.38)	0.027 (0.87)	0.002 (0.79)	-0.045 (-0.37)
Chronic or Severe Illness or Accident of Household Member	-0.280** (-2.36)	0.004 (0.16)	0.000 (0.15)	-0.280** (-2.35)
Death of Household Member	0.063 (0.68)	-0.042* (-1.94)	-0.004 (-1.31)	0.059 (1.12)
Death of Other Member of Family	-0.094* (-1.74)	0.015 (1.23)	0.001 (1.01)	-0.094*** (-3.05)
Hijacking, Burglary or Assault	-0.072 (-0.69)	-0.014 (-0.54)	-0.001 (-0.52)	-0.073 (-1.20)
Break-Up of Household	-0.154 (-1.29)	0.036 (1.23)	0.003 (1.01)	-0.150** (-2.14)
Other Idiosyncratic Shock	-0.598*** (-3.60)	0.016 (0.38)	0.001 (0.37)	-0.596*** (-6.05)
Other Unspecified Shock	0.087 (0.51)	0.034 (0.83)	0.003 (0.76)	0.090 (0.88)
Change in Conflict Intensity Index	-0.013* (-1.76)	0.001 (0.73)	0.000 (0.67)	-0.013*** (-2.96)
Log of Real Household Consumption Per Adult Equivalent	0.092* (1.78)	-	-	0.087*** (2.83)
Food Insecurity	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes

Time Fixed Effects	Yes	Yes	Yes	Yes
Regional Fixed Effects	Yes	Yes	Yes	Yes
N	17,461	17,475	17,461	17,461

Notes: Model estimated using a linear generalised structural equation model with fixed effects. Additional control variables, including time and region dummies, are included but not reported for brevity. Coefficients are reported to 3 decimal places. Z-statistics are reported to 2 decimal places and are in parentheses. Statistical significance indicated by * at the 10% level, ** at the 5% level, and *** at the 1% level. Full results available on request.

Chapter Three: To What Extent Did the South African Tobacco Sales Ban Affect Smokers' Mental Health?

1. Introduction

On 11 March 2020, the World Health Organisation (WHO) declared COVID-19, the infectious disease caused by the SARS-CoV-2 virus, a pandemic (WHO, 2020). In response., the South African government announced a three-week 'lockdown' starting on 27 March 2020, known as 'Alert Level 5'. This lockdown imposed strict measures, including stay-at-home orders and the cessation of the sale and production of non-essential goods (South Africa. Department of Co-operative Governance and Traditional Affairs, 2020). Tobacco products were classified as non-essential on 25 March, leading to a ban on their production and sale (van Walbeek *et al.*, 2021). This meant that smokers had less than two days to purchase cigarettes before the ban came into force. On 23 April 2020, an announcement was made that restrictions would be eased to 'Alert Level 4' from 1 May 2020. Initially, it was stated this would bring an end to the ban on tobacco products, however a U-turn was subsequently made on this decision (van Walbeek *et al.*, 2021). The ban continued through 'Alert Level 3' on 1 June 2020, finally ending on 18 August 2020. This meant that the sale of tobacco products was illegal for almost five months.

The tobacco sales ban faced significant controversy and two major legal challenges from tobacco companies. Criticism of the ban was also widespread in studies which examined its behavioural and market impact. Collectively, these indicated that the ban had largely been unsuccessful in its objective, with the majority of smokers continuing to smoke during the ban, purchasing cigarettes from the booming illicit tobacco market (van Walbeek *et al.*, 2020; van Walbeek *et al.*, 2021; van der Zee *et al.*, 2023). These studies unanimously deemed the ban a mistake: it not only led to a loss in tax revenue, but also undid progress made by the Illicit Economy Unit established in 2018 by further entrenching the illicit tobacco market.

There are reasons to suspect that the tobacco sales ban may have also affected the mental health and wellbeing of smokers. Qualitative evidence from a survey of smokers during the early weeks of the ban suggested there was an overwhelming sense of anger towards the ban, accompanied by reports of negative psychological impacts including increased feelings of anxiety and depression (van Walbeek *et al.*, 2020). This possibility merits more investigation.

To investigate the impact of the tobacco sales ban on smokers' mental health, this study utilised eight waves of individual-level panel data on South African adults. Data were drawn five waves of the National Income Dynamics Survey (NIDS) conducted from 2008 to 2017, and three waves of the Coronavirus Rapid Response Mobile Survey (NIDS-CRAM) conducted across 2020 and 2021. This provided observations on mental health and socioeconomic and demographic characteristics before, during, and after the tobacco sales ban. Employing difference-in-differences (DD) estimation with entropy balancing, we initially found a positive but non-significant effect of the ban on the frequency of depressive feelings of smokers. However, when distinguishing between pre-ban smokers who continued smoking during the ban and those who quit, a significant increase in the frequency of depressive feelings was observed among the former group. Additionally, a gender-based analysis indicated that predominantly female smokers exhibited elevated frequency of depressive feelings during the ban. Our findings are useful for policymakers interested in how best to reduce smoking rates within their populations, suggesting outright prohibition is not only ineffective but may also incur negative public health consequences. Furthermore, the findings emphasised the importance of providing accessible cessation support to smokers, not only to increase cessation rates but also to protect mental health.

The remainder of this chapter is structured as follows. Section 2 provides background information on smoking behaviour, the tobacco market, and the tobacco sales ban in South Africa. Section 3 reviews existing literature on the relationship between smoking and mental health, smoking cessation and mental health, gender differences in smoking motivation and cessation, as well as previous studies on the tobacco sales ban and the mental health impact of the COVID-19 pandemic in South Africa. Section 4 outlines the three hypotheses tested concerning the tobacco sales ban and smokers' mental health. Section 5 presents the data used for testing these hypotheses and descriptive statistics for our sample. Section 6 presents the baseline empirical specifications and estimation methods. Section 7 presents the results of testing the three hypotheses, along with various robustness checks. Finally, Section 8 concludes by summarising the results, discussing the strengths, limitations, and policy implications of the findings.

2. Background

This section provides background information on smoking behaviour and the tobacco market in South Africa, and on the tobacco sales ban introduced in March 2020 as part of the government's response to the COVID-19 pandemic.

2.1 Smoking Behaviour and the Tobacco Market in South Africa

Smoking prevalence amongst South African adults has been estimated to have fallen from approximately 32% in 1993 to 27% by 2000 (van Walbeek, 2002). This further declined to between 18% to 19% by 2017 (WHO, 2017; van Walbeek *et al.*, 2021). Significant variation in smoking prevalence exists between genders, with men consistently found to exhibit rates up to four times higher than women (van Walbeek, 2002; Reddy *et al.*, 2015). Heterogeneity in smoking rates have also been found between provinces, with the highest rates observed in Western Cape, Northern Cape, and Free State (Reddy *et al.*, 2015).

This decline in tobacco use has been partially attributed to the South African government introducing tobacco control policies, starting with the Tobacco Control Act of 1993 which banned smoking on public transport, and mandated of warning labels for packaging and advertising (Blecher, 2010). The act was amended in 1999, with the sale of tobacco products restricted to those aged over 16, and the prohibition of smoking in most public places, advertisement and sponsorship, and distribution of free products (Blecher, 2010). A further amendment was introduced in 2008, increasing the age of sale to 18 years old and banning tobacco sales at health and education establishments (Foundation for a Smoke-Free World, 2022). Aside from this legislation, increases in excise duties on cigarettes have also been attributed to contributing to declining smoking rates (van Walkbeek, 2002; Blecher, 2010).

The structure of the tobacco market has also significantly shifted during this period. Up until 2010, it was dominated by large multinationals, particularly British American Tobacco (BAT), with over 90% of the market share (van der Zee *et al.*, 2023). More recently, smaller domestic producers have reduced this dominance by undercutting prices and selling a significant proportion of their products through informal outlets (van der Zee *et al.*, 2023). Large multinationals have claimed this sizable portion of the market has been supplied by domestic producers largely through avoiding excise tax (Blecher, 2010; van der Zee *et al.*, 2023). The tobacco industry has long-claimed that increasingly high excise duties have driven the illicit tobacco market by encouraging cross-border smuggling from lower-priced neighbouring countries and incentivising tax evasion for domestic producers, although public health advocates have countered this by pointing to the fact that cigarette prices and taxes are higher in high-income countries where smoking is less prevalent

(Blecher, 2010). Overall, estimates for the size of the illicit market were as high as 30% in 2017 (van der Zee *et al.*, 2023). Partially in response to the growing illicit cigarette market, in 2018 the Illicit Economy Unit was created, although it is reported that this had only modest success in reducing the illicit tobacco market, which remained sizable when the tobacco sales ban was announced (van der Zee *et al.*, 2023).

2.2 The Tobacco Sales Ban

On 23 March 2020, South Africa's president announced a three-week 'lockdown' would commence from the 27 March in response to the emerging COVID-19 pandemic. This lockdown was denoted as being 'Alert Level 5', and, alongside other restrictions, ceased operations for all non-essential businesses and closed retail shops selling non-essential goods. On 25 March, tobacco products were announced as non-essential and thus their production and sale would be prohibited during the three-week lockdown (van Walbeek *et al.*, 2021). This announcement gave smokers less than two days' notice until the ban came into force. On 9 April 2020, it was announced that the Alert Level 5 restrictions would be extended for a further two weeks until at least 30 April. On 23 April, it was announced that restrictions would be eased to Alert Level 4 from 1 May. Initially, it was stated that this would include the end of the tobacco sales ban, however a U-turn was then made on this decision by the Minister of Cooperative Governance and Traditional Affairs (van Walbeek *et al.*, 2021). On 1 June, restrictions were lowered to Alert Level 3. However, the tobacco sales ban remained in place for a further two-and-a-half months until it was lifted on 18 August 2020 with the easing of restrictions to Alert Level 2. The tobacco sales ban was not re-introduced with future tightening of restrictions.

The government's rationale for the tobacco sales ban varied over time. Initially, they argued smokers would be more susceptible to COVID-19 due to the nature of the virus attacking the lungs. It was also argued that smokers would be at higher risk of transmission since smoking involves regular touching of the face. The decision to overturn the initial plan to end the ban on 1 May 2020 was centred around protecting the healthcare sector by preventing smokers from overwhelming healthcare facilities. Future arguments for extension of the ban were based on the notion that individuals tend to smoke in groups and share cigarettes, which increases the risk of transmission of the virus (van Walbeek *et al.*, 2021).

The tobacco sales ban lasted for more than 21 weeks, from 27 March 2020 to 18 August 2020. This was significantly longer than in Botswana and India, the only other two countries to impose similar bans for 12 weeks and 6 weeks respectively (van Walbeek *et al.*, 2021). Two major legal challenges against the ban were brought forward by representatives of tobacco companies. Most

notably when the country moved to Alert Level 3 on 1 June 2020 and tobacco sales remained prohibited, British American Tobacco South Africa (BATSA) filed a lawsuit against the South African government arguing the ban was unjustifiable and unconstitutional, and infringed on individuals' right to dignity. BATSA also argued that the negative consequences of the ban, such as the boom in illicit trade, outweighed any benefits, and that the rationale that the tobacco sales ban would help to prevent the healthcare system being overwhelmed was unfounded (van Walbeek *et al.*, 2021). In December 2020, four months after the ban had been lifted, the Western Cape High Court ruled in favour of BATSA, concluding that the tobacco sales ban could not withstand constitutional scrutiny and had been unnecessary (Southern Africa Legal Information Institute, 2020). The government appealed this decision to the Supreme Court of Appeal (SCA). This was dismissed in June 2022, with the SCA ruling the ban infringed on the fundamental rights of dignity, bodily and psychological integrity, freedom of trade, and deprivation of property. Furthermore, it ruled that the justifications presented by the government for the ban were limited and based on a lack of factual and scientific evidence (Southern African Legal Information Institute, 2022).

3. Literature Review

This section presents a review of the relevant literature. Section 3.1 provides an overview of the literature on the relationship between smoking and mental health, focussing primarily on papers exploring the direction of causality in this relationship. Section 3.2 then explores the relationship between smoking cessation and mental health, first examining short-run nicotine withdrawal and subsequently long-run cessation attempts. Section 3.3 presents gender differences in smoking behaviour found in the literature, paying particular attention to motivation for smoking and cessation success. Section 3.4 explores the existing literature on the tobacco sales ban in South Africa. Section 3.5 outlines empirical literature on the relationship between other anti-smoking policies and wellbeing. Section 3.6 follows by reviewing papers on the mental health impact of the pandemic in South Africa, with further reference to studies on other sub-Saharan African countries which paid attention to gender differences in mental health during the pandemic. Finally, Section 3.7 summarises the review and outlines the contribution this study makes to the literature.

3.1 The Relationship Between Smoking and Mental Health

Smoking and poor mental health have often been found to be correlated. However, there are competing explanations for the nature of this relationship. Four possibilities are:

i) Depression causes smoking – this is often attributed to the 'self-medication hypothesis', which posits that individuals with depression are more likely to smoke as they believe it alleviates symptoms of depression, which may be due to smokers misattributing the relief of nicotine withdrawal symptoms as genuine improvements to mental health (Fluharty *et al.*, 2016).

ii) Smoking causes depression – this has been attributed to the neurological impact of nicotine (Fluharty *et al.*, 2016), or alternatively to the social stigma surrounding smoking (Kang and Lee, 2010).

iii) There is a bidirectional relationship between smoking and depression – this posits that smoking and depression exhibit feedback loop in which they both cause the other to increase (Boden *et al.*, 2010).

iv) There is no causal relationship between smoking and depression – this suggests that the commonly observed correlation between the two is due to mutual confounding factors, such as genetics and environment (Tjora *et al.*, 2014).

The following papers were selected for this review as they aimed to test the evidence for these four possibilities.

Fluharty *et al.* (2016) conducted a review of 148 longitudinal studies exploring the relationship between smoking behaviours and depression and/or anxiety. The review found inconsistencies between papers in the nature of this relationship. Almost one-half of the studies found baseline depression and anxiety were positively associated with smoking behaviour, consistent with the self-medication hypothesis. However, one-third of the studies found evidence for the converse relationship, supporting the hypothesis that smoking increases susceptibility to depression and anxiety. It is noted these findings are not mutually exclusive, however, relatively few studies investigated the possibility of a bidirectional relationship between smoking and the two mental health outcomes. Of the sixteen that did, half found evidence for this possibility. No clear patterns emerged in the studies between genders or ethnicities. The authors suggested that these inconsistencies may have been partly driven by heterogeneity in the methods utilised by the papers, and recommended future studies employ methodologies allowing for stronger causal inferences to be made.

Considering this, we now discuss five studies employing more robust estimation methods to ascertain the direction of causality in the relationship between smoking and mental health. Tomita and Manuel (2020) utilised an incident cohort approach with four waves of the South African National Income Dynamics Study (NIDS) covering the period of 2008 to 2015. This approach aimed to isolate the impact of smoking on depression by excluding participants who exhibited significant presence of depression symptoms on the CESD-10 scale at their first observation point, and then right censoring participants who subsequently exhibited this level of symptoms in future waves. Using generalised equations with log links stratified by gender, the results indicated that smoking increased the risk of men aged 20 years and above exhibiting significant depressive symptoms but not women. For individuals aged 15 to 19 years, both men and women who smoke were at greater risk of exhibiting significant depressive symptoms, but the risk was more than double that for men than women. Although the authors controlled for known covariates of depression and smoking, they did not utilise fixed-effects regression methods to control for time-invariant genetic and environmental factors. The authors recommended future research should utilise longitudinal birth cohort studies or other methodologies such as Mendelian randomisation to allow for stronger causal inferences to be made.

Other papers in the literature have used alternative approaches which explicitly allow for the testing of a bidirectional causal relationship between smoking and depression. Liew and Gardner (2016) employed structural equation modelling (SEM) using a sample of 3,016 individuals from the 2007-2008 wave of the Indonesian Family Life Survey (IFLS). The results indicated that being a moderate to heavy smoker was associated with 4.3 times greater odds of exhibiting mild to severe

depression, whilst concurrently individuals with mild to severe depression were 2.9 times more likely to be moderate to heavy smokers. Although SEM addresses the potential endogeneity between smoking and depression, the causal inferences of the paper were limited by the cross-sectional nature of the data, meaning that at best it can be concluded that smoking and depression commonly co-occurred. Improving on this, Tjora *et al.* (2014) utilised latent modelling with a birth cohort sample derived from nine waves of the Norwegian Longitudinal Health Behaviour Study (NLHB). The results indicated there was a reciprocal process in the development of smoking and depression established in early adolescence, and that this relationship could not solely be explained by time-invariant characteristics such as common genetic and environment risk factors. Lastly, Wooton *et al.* (2020) employed a Mendelian randomisation (MR) approach which used genetic variants available in UK Biobank data to instrument for smoking initiation and duration to explore the direction of causality between smoking and depression and other mental health outcomes. The results showed evidence for a bidirectional effect between smoking and depression, with the causal effect from smoking to depression being larger than for the converse relationship.

The preceding studies provided evidence which generally supports the hypothesis that smoking causes mental health problems such as depression and anxiety, whilst there is also likely to be some reciprocity in this relationship. However, Magee and Clarke (2021) noted there is some preceding evidence that smoking can reduce psychological distress, postulating this may be due to the short-run effect of nicotine of enhancing positive mood and energy, aiding emotional regulation, and providing an instrumental coping mechanism to reduce stress. This possibility was tested using dynamic panel data modelling with the Americans' Changing Lives (ACL) survey of adults surveyed five times between 1986 to 2011. The findings showed that smoking appeared to reduce depressive symptoms once adjusting for a reciprocal positive effect of depressive symptoms on smoking status, but only amongst women. The authors suggested this was consistent with notion that smoking aids stress-related coping at least in women, a topic which is explored in further detail in Section 3.3. However, they also suggested this result may have been due the short-term mental health used, and that breaking the cycle of nicotine depletion and stress would likely improve long-term mental health. This finding highlights the importance of considering the relationship between smoking cessation and mental health.

3.2 The Relationship Between Smoking Cessation and Mental Health

This sub-section starts with a review of the evidence of the impact of short-run nicotine withdrawal on mental health. Subsequently, studies which have explored the long-run effects of successful and unsuccessful attempts at smoking cessation are examined.

The existing literature strongly suggests that short-run smoking cessation is associated with numerous psychological and physiological symptoms due to nicotine withdrawal. Indeed, the American Psychiatric Association's DSM-V classifies nicotine withdrawal as a mental disorder characterised by symptoms such as anxiety, depressed mood, irritability, and anger (American Psychiatric Association, 2013). A systematic review confirmed such outcomes as valid symptoms of nicotine withdrawal, further showing symptoms usually peak within the first week, with most lasting for two-to-four weeks (Hughes, 2007). Experimental studies have provided further evidence on the progression of both physiological and psychological symptoms in the first few hours of nicotine cessation (Morrell *et al.*, 2008; Leventhal *et al.*, 2013).

More pertinent to this study is the impact of long-term cessation. A review by Taylor *et al.* (2021) found comprehensive evidence that, at the very least, successful long-run cessation is not associated with worsened mental health outcomes, and indeed is likely to be associated with mental health benefits. Some studies have explored whether there are differences in mental health outcomes between those who successfully and unsuccessfully attempt to quit smoking. Berlin *et al.* (2010) was the first of these, producing the notable finding that smokers who relapsed in their quit attempts experienced adverse mood effects including increased depressive mood, anxiety, and suicidal ideation. Conversely, successful long-term cessation was associated with mental health improvements. The study was, however, limited by a small sample of only 134 individuals who were actively seeking treatment for smoking and had a history of mental disorders, and thus the generalisability of the findings beyond the sample are limited.

The result of Berlin *et al.*'s (2010) paper was dubbed the 'struggling quitters hypothesis' (SQH) by Capron *et al.* (2014), who further tested for this in another small U.S. sample which instead included individuals with and without a history of psychiatric disorders. The findings suggested that negative mental health effects from relapsing only occurred amongst the former. However, further studies using larger U.K. and Korean sample sizes found that relapsing smokers, regardless of their mental health history, exhibited increased levels of anxiety (McDermott *et al.*, 2013) and stress (Kim *et al.*, 2019) relative to continuing smokers, whilst the opposite was true for successful quitters. One possible explanation for the SQH is that smokers who attempt to quit but fail to do so may experience negative psychological feelings resulting from their disappointment in their failed quit attempt, coupled with withdrawal discomfort arising from struggling with urges to smoke for extended periods of time and then yielding to occasional relapses (Berlin *et al.*, 2010). This possibility is particularly important to consider in the context of our study, whereby many smokers may have attempted to quit during the tobacco sales ban.

3.3 Gender Differences in Smoking Motivation and Cessation

This section explores the literature on motivation for smoking and cessation success, paying particular attention to any gender differences that have emerged in these areas. Early studies utilised principal component analysis to derive important factors pertaining to perceived consequences from smoking (Livson and Leino, 1988; Brandon and Baker; 1991). Brandon and Baker (1991) produced a so-called 'Smoking Consequences Questionnaire' (SCQ) which could be administered to smokers and ex-smokers to measure the importance of these factors. The authors administered an 80-item developmental questionnaire to 382 US undergraduate current and ex-smokers and then utilised principal component analysis to generate a revised version capturing four factors pertaining to perceived smoking consequences. These four factors were 'negative consequences', pertaining to ill-health and negative social perceptions, 'positive reinforcement-sensory satisfaction', covering positive affect, craving reduction, and sensorimotor stimulation, 'negative reinforcement-negative affect reduction', covering perceived impact on reduction in factors such as irritability, anxiety, and depression, and 'appetite-weight control'.

Brandon and Baker (1991) subsequently examined gender differences in responses to the SCQ. This firstly indicated that current female smokers had higher scores for appetite-weight control and negative reinforcement. Furthermore, female ex-smokers had higher scores for negative reinforcement whereas male ex-smokers had extremely low scores on this factor. The authors suggested this implies women often continue to perceive that smoking can reduce negative affect, even when they are abstinent from smoking. As such, smoking may play a more important role for women in coping with negative affect, which suggests women may have more trouble quitting smoking than men. This echoed findings from other early US-based studies, including those of Livson and Leino (1998), who found women were more motivated to smoke for reduction of negative affect and pleasure than men, and Zuckerman *et al.* (1990), who found undergraduate women reported smoking more in emotionally stressful and social situations whereas men reported smoking more in situations requiring close attention to tasks. Subsequent studies have utilised similar frameworks for further exploration of gender differences in motivations for smoking in other populations.

Firstly, Berlin *et al.* (2003) administered a similar-style instrument to the SCQ to 330 French smokers, conducting factor analysis to derive a seven-factor model for perceived motivations for smoking. As with previous findings, the results showed that reasons for smoking differed between men and women, with women more likely to smoke for relaxation or to reduce tension, stimulation, and social smoking. Fidler and West (2009) used observations on 2,133 smokers from

the English Smoking Toolkit Study conducted in September 2007 to January 2008 to explore smoking motivations. The study found that across genders, enjoyment and stress relief were the most commonly stated motivations for smoking. However, women were more likely to report smoking for functional motives such as stress relief and weight control, whilst men were more likely to report smoking for hedonistic motives such as enjoyment. Finally, Pang *et al.* (2014) administered the SCQ to two samples of treatment and non-treatment seeking smokers from the US, again finding that females reported stronger negative affect reduction expectancies from smoking than males, with this being independent of other expectancies and mood and anxiety symptoms.

Thus, there is a consensus from the existing literature that women tend to be more likely to be motivated to smoke due to a perceived reduction of negative affect, implying a greater tendency to utilise smoking as a tool for coping with stressful situations. Women have also often been found to be less successful in smoking cessation than men (Ward *et al.*, 1997; Smith *et al.*, 2016), and this difference in smoking motivation between men and women has been cited as a possible explanation for this (Pang *et al.*, 2014). Indeed, experimental studies have found that women are more likely to report increased craving to smoke and faster consumption of a cigarette in response to induced negative mood (Perkins *et al.*, 2013; Weinberger and McKee, 2012), and more likely to report abstinence-induced increases in negative affect, withdrawal-related distress, and urges to smoke to relieve such distress (Leventhal *et al.*, 2007). Other gender differences in predictive factors of failure in cessation and/or relapse have also been found in the literature. For example, Westmaas and Langsam (2005) found that smoking at 4-month follow-up after a cessation attempt was negatively predicted by seeking of social support amongst women but not men, whilst McKee *et al.* (2003) found that female ex-smokers were more likely to relapse in response to adverse financial advents, and female current smokers were more likely to continue smoking following adverse financial and health events compared to men. Finally, some studies have found that women are generally just less confident in their ability to quit than men, which may help to explain this potential disparity in successful cessation (Audrain *et al.*, 1997; Etter *et al.*, 2002).

3.4 The Tobacco Sales Ban in South Africa

The section explores the literature on the tobacco sales ban in South Africa. Most studies on the ban have predominantly focussed its impact on smoking behaviour and the tobacco market.

van Walbeek *et al.* (2020) produced one of the first reports on the tobacco sales ban, published on 15 May 2020 whilst the ban was still on-going. The authors analysed 12,204 responses to a survey distributed by the Research Unit on the Economics of Excisable Products (REEP) to regular

cigarette smokers between 29 April and 11 May 2020. The survey primarily focussed on the market and behavioural impact of the ban, although an open-ended question was also posed to smokers for them to comment on their perceptions of the ban. Approximately 41% of smokers indicated they had attempted to quit smoking during the ban, although only 16% reported they had successful quit smoking at the time of the survey. Findings suggest that despite the ban, smokers were still able to purchase cigarettes through informal outlets, however they faced hyperinflated prices. A thematic analysis was conducted on the comments provided by 5,831 participants. Most comments (77%) fell under the theme of anger, with smokers citing factors such as being unable to stock up sufficiently before the ban, having to smoke undesirable products, and feeling rights had been infringed upon. Anger was also directed towards being unable to rationalise the ban, with respondents citing frustrations over the perceived economic and health illogicality of the ban. The authors postulated that the U-turn on the decision to lift the tobacco sales ban with the relaxation of lockdown restriction to Alert Level 4 in May would likely have contributed to the large amount of anger expressed by smokers. Negative mental health effects were expressed in 1,309 comments, of which 74% indicated increased feelings of anxiety, 4% indicated increased severity and/or duration of depressive episodes, and 22% experienced a reduction in ability to concentrate. Further exploration into the psychological impact of the ban on smokers is warranted, with quantitative methods able to provide a more robust estimate for the magnitude of this impact.

Subsequent studies have been conducted with samples of smokers surveyed over the entirety of the ban and after it was lifted. Two further REEP surveys were conducted from 4 to 19 June (during the ban) and from 16 September to 5 October (after the ban). However, none explored the mental health impact of the ban, instead continuing to focus on behavioural and market impacts. van der Zee *et al.* (2023) analysed these surveys, finding 9% of pre-lockdown smokers reported they had successfully quit during the ban, a lower figure than the 16% found in the first REEP survey suggesting some smokers may have relapsed as the ban continued. Cigarette consumption fell during the ban by an average of 18% between March and June 2020, whilst the average retail price of cigarettes increased in this period by over 240%. Thus, concurrent with Van Walbeek *et al.*'s (2020) findings from the first REEP survey, the ban continued to be unsuccessful in preventing smokers buying cigarettes even as it continued for a further three months. The authors suggested that that smokers may have been discouraged to quit due to the many anxieties and stressors caused by the pandemic.

The market impact of the ban was also explored by Van Walbeek *et al.* (2021) using the information from wave five of the South African NIDS, conducted in 2017, and the third wave of NIDS Coronavirus Rapid Mobile Survey (NIDS-CRAM) conducted between November and December

2020. Beyond allowing the authors to look retrospectively at the impact of the sales ban, another advantage of this data was that it encompassed a broadly nationally representative sample, unlike the REEP surveys analysed by the preceding papers. Both waves of data contained specific modules on smoking behaviour, with the NIDS-CRAM posing questions referring to behaviour before, during, and after the ban. Of the 6,130 NIDS-CRAM respondents, 729 indicated they had smoked cigarettes in the week prior to lockdown on 27 March 2020. Of these 729 individuals, 585 admitted to continuing smoking during the ban, whilst 590 individuals in the NIDS-CRAM stated they had smoked cigarettes in the past week (*i.e.*, approximately 3 months after the ban had been lifted), a slight increase compared to the during-ban period suggesting some individuals had relapsed. The study estimated that cigarette consumption fell by approximately 2.3 billion during the ban. Using a rule of thumb estimate of one tobacco-related death per million cigarettes smoked, this suggests than 2,300 premature tobacco-related deaths were averted. Despite this health impact clearly being positive, the authors believed the ban had still been a mistake. First noted was the loss of tobacco excise tax revenues, estimated to be approximately R5.8 billion by the paper. Second, it was suggested that the introduction of the sales ban entrenched new illicit distribution channels into the market, undoing much of the progress made by the introduction of the Illicit Economy Unit. The authors therefore argued that a steep increase in excise tax on tobacco products at the start of lockdown would have been a better policy to pursue, being likely to achieve a similar outcome in reduction of cigarette smoking but with simultaneous tax revenue gains.

Finally, van Walbeek *et al.* (2023) published further findings from the fifth wave of the NIDS and the third wave of the NIDS-CRAM focussing explicitly on quitting behaviour during the tobacco sales ban. Based on longitudinal analysis of both the NIDS and NIDS-CRAM data, they estimated that 7% of individuals who smoked in the fifth wave of the NIDS, conducted in 2017, quit during the ban, but over 70% of them subsequently relapsed after it was lifted. The authors continued to argue that the ban did not lead to large-scale smoking cessation, reflecting a failure to provide smokers with adequate cessation support and the inability to control the illicit tobacco market both pre- and during the ban.

Thus, all evidence suggests that despite the tobacco sales ban, most pre-ban smokers in the South African population continued to smoke, relying on existing stocks and purchasing cigarettes from the booming illicit market. The main impact of the ban therefore was not to protect public health, but to lead to significant disruption of the tobacco market. Cigarette prices experienced hyperinflation, whilst non-MNC cigarette brands saw massive market gains at the expense of the previously dominant large MNCs. Post-ban evidence tentatively suggests that some smokers may

have successfully given up, but some who had quit during the ban relapsed when it was lifted. All papers unanimously agreed the ban had been a mistake, having led to further entrenching of the illicit market whilst simultaneously eliminating all tobacco excise revenue. Furthermore, qualitative analysis from one study suggests that the ban may have had a negative mental health impact, with smokers expressing significant levels of anger at the ban and reporting increased feelings of anxiety and depression (van Walbeek *et al.*, 2020). However, this was not explored further by other papers. Thus, there is a need for more robust quantitative analyses to be conducted to estimate the magnitude and significance of the impact the ban had on South African smokers' mental health.

It should be noted that shorter tobacco sales bans were also implemented in two other countries, India and Botswana, in response to the COVID-19 pandemic. However, the mental health impact of these bans on smokers has not been studied by the existing literature, with the primary focus on behavioural outcomes relating to quitting and cessation rates (Veeraiah *et al.*, 2021; Gupte *et al.*, 2020). One cross-sectional study from India did estimate prevalence rates and determinants of anxiety and depression amongst tobacco users during the first Indian COVID-19 lockdown, however the impact of the tobacco sales ban itself on these rates was not investigated (Bassi *et al.*, 2022).

3.5 Other Tobacco Control Policies and Mental Health and Wellbeing

A small literature has empirically explored the impact of other tobacco control policies on mental health and wellbeing, including excise duty increases and the implementation of bans on smoking in public places such as in workplaces or hospitality locations. Despite public place bans being less severe than South Africa's outright tobacco sales ban, these studies propose and test some mechanisms which hold relevance to the South African context.

Hinks and Katsaros (2012) conducted an early study examining the impact of public smoking bans on smokers' wellbeing. The authors noted that such a ban could be considered a negative shock to smokers and outline some possible mechanisms through which this would affect their wellbeing. Firstly, under Becker's theory of rational addiction, a ban would increase the 'cost' of smoking to smokers and thereby reduce consumption, leading to a permanent decrease in smokers' wellbeing. Alternatively, the impact of the ban may only be transitory should individuals' utility eventually revert to some 'set-point' following the 'shock' of the ban. Additionally, there may be a reduction of possible positive social externalities from being a smoker, as well as smokers' perceiving a ban as an infringement on their personal liberties. The authors test these possibilities using three waves of the British Household Panel Survey (BHPS) from 2005 to 2007, focussing on the change in cigarette consumption exhibited by smokers pre- and post-ban. Utilising OLS regression models

for life satisfaction, the study firstly found smokers who reduced their cigarette consumption in the period immediately after the ban reported lower levels of life satisfaction than those who consumed the same number of cigarettes. The authors argue this is consistent with the notion that smokers feel their individual liberties were threatened by the ban. Additional analyses indicated this reduction in life satisfaction was only reported by heavy smokers (10 or more cigarettes per day) who reduced their consumption following the ban. However, heavy smokers who reduced their cigarette consumption then exhibited increased life satisfaction in the second year after the ban, suggesting only a transitory impact of the ban on wellbeing. These findings are limited by the methodology failing to control for individual-level heterogeneity.

Leicester and Levell (2016) note it has often been assumed that anti-smoking policies would improve social welfare but harm smokers' wellbeing. However, it is possible smokers could benefit from anti-smoking interventions if they hold time inconsistent preferences, meaning they do not act in their own best interests when making smoking decisions. Indeed, the authors argue that many smokers plan to give up smoking in the future but are unable to follow through with these plans. Thus, anti-smoking policies may serve as a commitment device to smokers to aid them with giving up smoking. Under such a framework, higher future costs of smoking imposed by anti-smoking policies may provide a commitment 'benefit' to smokers, ultimately reducing their future consumption to 'optimal' levels. To explore this, the authors conducted an empirical study using individual-level longitudinal data from the BHPS from 1991 to 2008. The study utilised DD models to estimate the impact of anti-smoking policies on smokers' self-reported wellbeing, exploiting time-specific variation in cigarette taxation, and regional variation in the date of smoking bans in public places whereby Scotland implemented a ban prior to other parts of the UK. The authors found consistent evidence that higher excise taxes increased the wellbeing of smokers, albeit this was relatively small in magnitude. Conversely, the implementation of bans on smoking in public places was not found to significantly impact wellbeing. The authors suggested that bans may be less effective as commitment devices than increases in taxes as smokers can substitute smoking more away from public places. Furthermore, the 'hassle' of complying with the ban may have negated any benefits induced by the ban acting as a self-control device.

Odermatt and Stutzer (2015) also tested the possibility of public smoking bans acting as commitment devices to smokers by utilising repeated cross-section data from 41 waves of the Eurobarometer survey on individuals from 40 European countries to explore the impact of various smoking bans on the SWB of both smokers and non-smokers. The authors noted that such bans may have competing mechanisms for both these groups. For non-smokers, bans may be expected to have positive effects on health due to protection from second-hand smoke, however, negative

side effects may occur if they lead to the displacement of smoking from public places to private places. For smokers, bans may negatively impact their SWB as they constrain their habit. However, as also outlined by Leicester and Levell (2016), a ban may positive impact the SWB of individual smokers who face self-control problems if the ban acts as a self-control device. Little evidence was found for the introduction of bans being associated with SWB, except for a positive correlation for smokers who indicated they would like to quit smoking. Thus, unlike Leicester and Levell (2016), this latter result provided some evidence for the notion that bans can act as self-control devices, but only amongst smokers with a pre-existing desire to quit. The study also estimates the relationship between cigarette prices a SWB, finding that converse to Leicester and Levell (2016), increased prices were negatively associated with SWB for smokers, thereby suggesting their inefficacy as self-control devices.

Finally, Yang and Zucchelli (2018) also utilised the BHPS to explore the impact of the bans on smoking in public places on wellbeing. The authors noted that previous studies have found mixed evidence of bans improving wellbeing of smokers, however these studies have neglected the possibility of intra-household wellbeing externalities, and furthermore have not fully accounted for individual-level unobserved heterogeneity. Addressing this, the authors estimated flexible DD models combined with propensity score matching to explore the impact of smoking bans on the SWB of smokers, non-smokers, and couples of different types of smokers. The study firstly found when considering both never smokers and potential smokers (defined as individuals who reported smoking at least once during the survey) as a single group, the implementation of the ban had a positive impact on the SWB of married individuals, particularly married women. Positive and statistically significant SWB effects generally found for never-smoker individuals in a couple (with or without a spousal never smoker) for both genders. Conversely, for potential smokers in a couple (with or without a spousal potential smoker), although the estimated treatment effects of the ban were similar in magnitude to those of never smokers, they were not statistically significant. However, the authors argue this may be due to the larger standard errors resulting from the smaller number of observations available to estimate these models. Further heterogeneity analysis found larger increased in SWB for married women with dependent children, but no such effect for male equivalents. Additional analysis further decomposed smokers into always smokers, current smokers, and post-ban quitters. This found the ban had a statistically significant positive effect on the SWB of married women who were always smokers or current smokers, and for married men who were quitters. Throughout all models, statistically insignificant effects of the ban were found for individuals who were single. Taken together the results imply the implementation of a public smoking ban may have positive wellbeing externalities for married couples, particularly women

with dependent children. Furthermore, an increase in wellbeing was estimated for married men who quit smoking after the introduction of the ban, which the authors suggest may be consistent with the notion that bans can act as a commitment device.

Thus, there is varying evidence in the literature that the introduction of smoking bans in public places may serve as commitment devices for smokers to quit smoking, thereby leading to improvements in mental health and wellbeing at least amongst some groups. However, the public place smoking bans considered by these studies are considerably less stringent than the outright ban on the sale of tobacco imposed by the South African government.

3.6 Mental Health and Other Health Impacts of the COVID-19 Pandemic in South Africa

Alongside the tobacco sales ban, the South African government introduced numerous other restrictions on freedom of movement, business, and other social activities in the national lockdown that commenced on 27 March 2020. The severity of restrictions was subsequently adjusted throughout the course of the pandemic with a level system. It is therefore important to consider studies which explored the mental and general health of South Africans during this period, as any effects of the smoking ban on mental health may be confounded by general effects of the pandemic.

The studies reviewed utilised a variety of methodologies and localised (Kim *et al.*, 2020; De Man *et al.*, 2022), nationally representative (Hunt *et al.*, 2021; Posel *et al.*, 2021; Oyenubi *et al.*, 2022; Ohrnberger, 2022; Oyenubi and Kollamparambil, 2022; Ntuli and Kwenda, 2023), and multinational (Greyling *et al.*, 2021; de la Rosa *et al.*, 2022) samples. Taken together, the findings suggest that the mental and general health of South Africans suffered during the pandemic. Empirical evidence indicated contributing factors to poorer health outcomes included perceived risk of COVID-19 infection (Kim *et al.*, 2020; De Man *et al.*, 2022; Oyenubi *et al.*, 2022), food insecurity and hunger (Hunt *et al.*, 2021), lockdown-related unemployment without pay (Posel *et al.*, 2021), and lockdown-induced job and income loss (Ohrnberger, 2022; Oyenubi and Kollamparambil, 2022). Qualitative evidence also suggested a myriad of factors may have contributed to the mental health impact of the pandemic, including distress caused by physical, social, cultural, and environmental factors, alongside initial panic, and fear of the unknown. Furthermore, individuals have cited their inability to access normal coping mechanisms due to lockdown restrictions on visiting family and places of worship as impacting their mental health (Rwafa-Ponela *et al.*, 2022). This is an important consideration given that smokers may use cigarettes as a coping mechanism during stressful events, and therefore prohibiting access to them could exacerbate psychological distress responses to the pandemic.

Only five studies explicitly explored the impact of COVID-19 policies on mental health and other health outcomes, of which two compared the differing level of national policy stringency in South Africa to other countries (Greyling *et al.*, 2021; de la Rosa *et al.*, 2022), two explored change in depressive symptoms as policy stringency eased in South Africa between in the second half of 2020 (Oyenubi and Kollamparambil, 2021; Ntuli and Kwenda, 2023), and one examined the mitigating impact of South Africa's Child Support Grant (CSG) programme on the effect lockdown-induced income shocks on self-rated health (Ohrnberger, 2022).

Studies using multinational data found that at an aggregated-level, South Africans may have suffered more during the first few months of the pandemic relative to other countries from imposing more stringent lockdown policies. For example, Greyling *et al.* (2021) found that South Africa exhibited a greater decline in Gross National Happiness (GNH) (measured through analysis of sentiment of tweets during the first half of 2020 compared to 2019) compared to New Zealand and Australia (for which stringency declined respectively). Similarly, in a nine-country analysis of Google Trends search terms related to mental health, South Africa was one of three countries to exhibit increased searches for 'anxiety' during lockdown restrictions (alongside Spain and India, both of whom imposed relatively strict regulations) and one of two countries to exhibit increased searches for 'suicide' (de la Rosa *et al.*, 2022). Thus, it appears as though South Africans mental health may have suffered from the high stringency of COVID-19 policies implemented on 27 March 2020.

Interestingly, analyses of the NIDS-CRAM second (June-August 2020) and third (November-December 2020) waves found that depressive symptoms amongst the general population (Oyenubi and Kollamparambil, 2021) and formal and informal workers (Ntuli and Kwenda, 2023) actually increased in this period despite the easing of COVID-19 restrictions. Oyenubi and Kollamparambil (2021) showed this rise in depressive symptoms could largely be attributed to those with low socioeconomic status, perhaps due to the impending roll-back of social security grant top-ups and a significant increase in essential food prices during this period.

Finally, several studies found that women may have been particularly susceptible to poorer mental health during lockdown restrictions in South Africa. Utilising a mixture of qualitative and quantitative methods on both cross-sectional and longitudinal samples including young women (Duby *et al.*, 2022), pregnant women (Abrahams *et al.*, 2022), and women residing in socioeconomically deprived areas (Mahlangu *et al.*, 2022), these studies indicated that many women experienced increases levels of stress, anxiety, depression, and other common mental health disorders. Contributing factors to this included increased fear and occurrence of domestic violence

and sexual abuse, food insecurity, and economic stress during the pandemic (Ndlovu *et al.*, 2022; Duby *et al.*, 2022; Abrahams *et al.*, 2022; Mahlangu *et al.*, 2022). Similar findings were drawn from other samples of women in Sub-Saharan Africa, including Tanzania (Stockl *et al.*, 2023), Uganda (Miller *et al.*, 2022), and Kenya and Nigeria (Mueller *et al.*, 2023). Additional risk factors for women's mental health during periods of lockdown identified including increased domestic burden (Mueller *et al.*, 2023). However, one study with pre- and post-lockdown data available in Tanzania found that whilst rates of ill mental health amongst women increased during lockdown, they subsequently declined below pre-COVID-19 levels with the lifting of lockdown restrictions (Stockl *et al.*, 2023).

3.7 Contribution of This Study

The preceding literature review indicated that whilst the market and behavioural impact of the tobacco sales ban has been comprehensively studied (van Walbeek *et al.*, 2020; van Walbeek *et al.*, 2021; van der Zee *et al.*, 2023; van Walbeek *et al.*, 2023), the mental health impact on smokers has largely been neglected. Qualitative evidence from one survey suggested that smokers were angered by the ban and reported that their mental health had suffered through increased feelings of anxiety and depression (van Walbeek *et al.*, 2020). However, this finding came from a non-nationally representative survey which was conducted during the first weeks of the ban, and therefore provided no indication as to whether these mental health impacts persisted throughout the ban, nor whether smokers' mental health subsequently recovered with the lifting of the ban. Furthermore, as this is only a qualitative finding, no estimate of the magnitude or significance of the possible mental health effect of the ban on smokers is provided. Further investigation into the mental health impact of the ban using more robust quantitative methods is therefore merited.

As such, this study utilised longitudinal individual-level panel data from a nationally representative household survey. This was advantageous in providing data on the mental health of smokers before, during, and after the ban, and as such we could better estimate and quantify the causal impact of the ban on their mental health. We further contribute to the literature by exploring if there was a differential impact of the ban on the mental health of smokers who reported successfully quitting during the ban versus those who continued to smoke. This provided a novel opportunity to explore the potential mechanisms linking the ban to smokers' mental health, such as the struggling quitters hypothesis (Berlin *et al.*, 2010; Capron *et al.*, 2014) and the role of cigarettes as a coping mechanism in response to stressors (Livson and Leino, 1988; Zuckerman *et al.*, 1990 Brandon and Baker, 1991; Berlin *et al.*, 2003; Fidler and West, 2009; Pang *et al.*, 2014). Finally, several studies both from South Africa and other sub-Saharan African countries have indicated

that women were more susceptible to negative mental health effects during the pandemic, for reasons such as food insecurity, economic stress, and domestic burden, alongside confined conditions increasing the risk of domestic violence (Ndlovu *et al.*, 2022; Duby *et al.*, 2022; Abrahams *et al.*, 2022; Mahlangu *et al.*, 2022; Mueller *et al.*, 2023; Stockl *et al.*, 2023). By conducting heterogeneity analysis between female and male smokers during the ban, this study further contributes to the literature on factors which may help explain why women's mental health generally suffered more during the pandemic in South Africa. It is important to ascertain this possible impact not only from a public health perspective, but also in the context of future formulation of smoking policies.

4. Hypotheses

This section outlines the three hypotheses tested in the analysis, which aimed to determine the impact of the tobacco sales ban in South Africa on the mental health of smokers.

Qualitative evidence from one survey suggested that smokers were angered by the ban and reported that their mental health had suffered through increased feelings of anxiety and depression (van Walbeek *et al.*, 2020). The existing literature also indicated that smokers are already more likely to have poor mental health than non-smokers (Tjora *et al.*, 2014; Tomita and Manuel, 2016; Liew and Gardner, 2016; Fluharty *et al.*, 2016; Wootton *et al.*, 2020). Further evidence suggested the mental health of the general South African population suffered during the pandemic (Kim *et al.*, 2020; De Man *et al.*, 2022; Greyling *et al.*, 2021; Hunt *et al.*, 2021; Posel *et al.*, 2021; de la Rosa *et al.*, 2022; Oyenubi *et al.*, 2022; Rwafa-Ponela *et al.*, 2022; Oyenubi and Kollamparambil, 2022). It is therefore reasonable to postulate that smokers' may have been particularly vulnerable to poorer mental health with the introduction of the ban for several reasons.

Firstly, it is likely smokers felt unfairly targeted by the policy, for which there was little-to-no medical justification, viewing the ban as an infringement on their personal freedom. In fact, this was a conclusion drawn by the South African Supreme Court of Appeal (ACA), who ruled in June 2022 that the ban infringed on the fundamental rights of dignity, bodily and psychological integrity, and that the justifications presented by the government for the ban were based on a lack of factual and scientific evidence (Southern African Legal Information Institute, 2022). Perceived infringements on rights have been suggested as a mechanism linking less stringent public smoking bans to poorer wellbeing for smokers (Hinks and Katsaros, 2012), and other COVID-19 policies with poorer mental health in other countries (Toffolutti *et al.*, 2022).

Second, the ban may have restricted access to a possible coping mechanism during the stress of the pandemic. Indeed, the literature on smoking motivation suggests that stress relief is one of the primary consequences of cigarette consumption cited by smokers (Fidler and West, 2009; McDermott *et al.*, 2013). Qualitative evidence suggests that the inability to access usual coping mechanisms due to other COVID-19 restrictions may have contributed to South Africans experiencing elevated levels of mental distress (Rwafa-Ponela *et al.*, 2020).

As such, we proposed the following as the first hypothesis to be tested:

H1: The tobacco sales ban induced increased frequencies of depressive feelings amongst smokers.

Next, evidence suggests that whilst a small proportion of smokers successfully quit smoking during the ban, many were unsuccessful in their attempts (van Walbeek *et al.*, 2020; van Walbeek *et al.*, 2022; van der Zee *et al.*, 2023; van Walbeek *et al.*, 2023). There are several reasons to expect that there may have been a differential impact of the ban on those who managed to quit versus those who continued to smoke.

Firstly, individuals defying the ban either had to rely on existing stocks or utilise the illicit tobacco market. Turning to the illicit tobacco market may have several implications for smokers. They would face significantly higher prices for cigarettes, with estimations of price increases exceeding 240% (van der Zee *et al.*, 2023). This may cause financial strain at a time when individuals may have been facing income and employment uncertainty during the pandemic (Posel *et al.*, 2021; Ohrnberger, 2022; Oyenubi and Kollamparambil, 2022). Further, it may make otherwise law-abiding citizens feel like criminals as they turn to the underground market, whilst the threat of punishment or condemnation if being found breaking the sales ban may also bring negative psychological consequences. Individuals may also feel as though they are 'letting the country down' by breaking COVID-19 restrictions. Indeed, an analysis of speeches by leading political actors across the world found COVID-19 is portrayed as the 'out-group' in society and pushed the notion of the 'nation-as-a-team' as the 'in-group' fighting against the virus (Berrocal *et al.*, 2021). Reflecting this, evidence from several European countries indicated most individuals believed there is justification for the condemnation of rule-breakers in society who are perceived as going against the collective effort to overcome the virus (Bor *et al.*, 2023).

Second, analyses of surveys of smokers conducted during the ban have indicated that whilst up to 41% of smokers attempted to quit when the ban was first implemented, only 16% were successful by May 2020, with this figure as low as 7% by the end of the ban (van Walbeek *et al.*, 2020; van der Zee *et al.*, 2023; van Walbeek *et al.*, 2023). This implies a significant proportion of smokers had relapsed from initial cessation attempts over the course of the ban. There is evidence from the literature that such relapses can negatively impact mental health per the 'struggling quitters hypothesis' (Berlin *et al.*, 2010; McDermott *et al.*, 2013; Capron *et al.*, 2014, Kim *et al.*, 2019). One mechanism suggested for explaining this is that relapsing induces negative psychological feelings due to the disappointment of failure in a quit attempt (Berlin *et al.*, 2010). This disappointment may even be magnified in the context of the ban, whereby relapsing not only breaks the smokers' own quit attempt, but also the law.

For some smokers, the introduction of the ban may be seen as a commitment device to quit smoking (Odermatt and Stutzer, 2015; Leicster and Levell, 2016; Yang and Zucchelli, 2018). The effect of the ban on quitters on is likely to be conditional on how long they had successfully quit smoking. During the early weeks of the ban, quitters would likely suffer from psychological effects associated with nicotine withdrawal (Hughes, 2007). Indeed, some of those who provided responses to the first REEP survey conducted during the early ban period referred to such withdrawal effects (van Walbeek *et al.*, 2020). They may also have suffered if smoking was one of their coping mechanisms, particularly given the stressors associated with strict lockdown and general pandemic conditions in the first few weeks of the ban. Finally, they would likely have felt as equally, if not more, aggrieved as those who continued to smoke by seemingly unjustified implementation of the ban. However, in the long run, given that nicotine withdrawal symptoms typically reside within one month (Hughes, 2007), it is plausible that the ban may even had positively impacted the mental health of those who were successful in quitting. Indeed, Yang and Zucchelli (2018) found some evidence that the ban on smoking in public places in the UK led to improved wellbeing for married men who quit following its implementation.

As such, we proposed the following second hypothesis to be tested:

H2: The tobacco sales ban induced a larger increase in frequency of depressive feelings in continuing smokers relative to those who quit during the ban.

Finally, previous findings from the literature suggest there may have been a heterogeneous impact of the tobacco sales ban on mental health between men and women. Given evidence that women are more likely to smoke to reduce negative affect (Livson and Leino, 1988; Zuckerman *et al.*, 1990 Brandon and Baker, 1991; Berlin *et al.*, 2003; Fidler and West, 2009; Pang *et al.*, 2014), then restricted access to tobacco may generally induce greater negative changes to women's mental health compared to men. Women are also more likely to smoke to cope with stressful events, and as such may be more susceptible to negative mental health effects given the likely stressors caused by the pandemic. Indeed, evidence from both South Africa and other sub-Saharan African countries indicates that many women reported declines in their mental health due to lockdown conditions increasing stressors such as food insecurity, economic stress, and domestic burden, alongside confined conditions increasing the risk of domestic violence (Ndlovu *et al.*, 2022; Duby *et al.*, 2022; Abrahams *et al.*, 2022; Mahlangu *et al.*, 2022; Mueller *et al.*, 2023; Stockl *et al.*, 2023).

There is also some evidence that women are less likely to successfully quit smoking than men (Ward *et al.*, 1997; Smith *et al.*, 2016), and there is reason to suspect that this difference may continue or even be exacerbated in the context of the tobacco sales ban and the wider pandemic.

For example, women have been found more likely to relapse or continue smoking in response to adverse financial and health events (McKee *et al.*, 2003). Additionally, successful long-term smoking cessation has been found to be positively predicted by social support for women but not men (Westmaas and Langsam, 2005), and access to this support would likely have been significantly restricted by other COVID-19 regulations imposed alongside the tobacco sales ban. If women were indeed less likely to quit smoking or more likely to relapse during the ban, then we may expect the mechanisms postulated above linking continued smoking during the ban to poorer mental health outcomes to be particularly applicable to women. Furthermore, some evidence suggests that women who relapse from smoking cessation attempts are at a higher risk of poorer mental health than men (Kim *et al.*, 2019).

As such, we test proposed the following as the third hypothesis to be tested:

H3: The tobacco sales ban induced a larger increase in frequency of depressive feelings in female smokers relative to male smokers.

5. Data and Descriptive Statistics

This section begins by providing details of the data we used our hypotheses. This is followed by a presentation of the descriptive statistics for the characteristics of the sample we utilised in our analysis.

5.1 Data

We first present an overview of the South African National Income Dynamics Study (NIDS) and the follow-up National Income Dynamics Study – Coronavirus Rapid Mobile Survey (NIDS-CRAM). Subsequently, details on the variables constructed are provided.

5.1.1 The National Income Dynamics Study (NIDS)

The National Income Dynamics Study (NIDS) is a household panel survey conducted in South Africa. Data collection began in 2008, with four subsequent waves conducted in 2010/11 (wave 2), 2012 (wave 3), 2014/15 (wave 4), and 2017 (wave 5). The survey is implemented by the Southern African Labour Development Research Unit (SALDRU). The first wave of the survey was completed by a broadly nationally representative sample of more than 28,000 individuals from 7,300 household across all regions of South Africa. Subsequently, the survey was administered in two-year intervals to the same participants. Due to attrition, particularly amongst White, Asian, and high-income respondents, a top-up sample of 2,775 individuals was introduced in wave 5 (Brophy *et al.*, 2018).

The study collects a wide range of socioeconomic and demographic information on respondents at both an individual and household level. Topics covered at the individual level include demographics, labour market participation, individual income from non-employment sources, receipt of government grants, education, tobacco and alcohol use, health, emotional health and mental wellbeing, personal ownership and debt, and social cohesion. At the household level, information was elicited on household living standards, food and non-food consumption, ownership of durable goods and household net assets, negative events experienced by the household, and agricultural activities.

5.1.2 The Coronavirus Rapid Mobile Survey (NIDS-CRAM)

The NIDS-CRAM was a follow-up to the NIDS utilising a sub-sample of individuals who were aged 18 years or above and observed in wave 5 (2017) of the NIDS. Wave 1 of data collection took place between 7 May and 27 June 2020, with a total of 7,073 respondents successfully interviewed. The second wave of data collection took place between 13 July and 13 August 2020. As there was an attrition rate of approximately 19% between waves 1 and 2, a top-up sample of

1,084 individuals randomly sampled from the NIDS wave 5 was introduced in wave 3, which took place between 2 November and 13 December 2020 (Ingle *et al.*, 2021). It should be noted that unlike with the NIDS, this attrition in the NIDS-CRAM appeared to be random (Daniels *et al.*, 2020). Interviews for the fourth wave took place between 2 February and 10 March 2021, whilst the fifth wave was collected between 6 April and 11 May 2021.

Contrasting the NIDS which used face-to-face interviewing, the NIDS-CRAM employed Computer Assisted Telephone Interviewing surveys to collect information from respondents. Only an individual-level questionnaire was administered, which was significantly shorter than those used in the NIDS. However, sufficient information was collected across a range of demographic and socioeconomic topics for the purpose of this study. Thus, individuals from the NIDS and NIDS-CRAM can be combined into an unbalanced panel consisting of 10 waves of data covering the period from 2008 until mid-2021.

5.1.3 Description of Variables

Table 5.1 provides details on the variables utilised in the analysis. This includes a description of the variable, additional notes on how the variable was constructed from the NIDS and NIDS-CRAM datasets, the type of variable, the waves for which the variable is available, and the expected association the variable would exhibit with our measure of mental health.

5.1.3.1 Frequency of Depressive Feelings

The NIDS and NIDS-CRAM contained different measures of individuals' mental health, the CESD-10 and the PHQ-2 respectively. As such, a direct comparison of scores on the full scales was limited. However, both scales contained an item referring to recent frequency of depressive feelings. Although not identical, the wording of the questions was similar, and both were measured on 4-point scales with comparable interpretation of the possible responses. In the NIDS, individuals were asked to state how often they have felt "Depressed" during the past week. The four possible responses were "Rarely or none of the time (less than 1 day)", "Some or little of the time (1-2 days)", "Occasionally or a moderate amount of the time (3-4 days)", or "All of the time (5-7 days)". These responses were, respectively, coded as an ordinal variable equal to 0, 1, 2, and 3, with this information elicited in all five waves of the NIDS. In the NIDS-CRAM, individuals were asked "Over the past 2 weeks, have you been feeling down, depressed, or hopeless?". The four possible responses were "Not at all", "Several days", "More than half the days", or "Nearly every day". Similarly, these responses were coded as an ordinal variable equal to 0, 1, 2 and 3 respectively. This variable was available in waves 2, 3 and 5 of the NIDS-CRAM. The information from the NIDS and NIDS-CRAM was then combined into a single variable on a 4-point scale

reflecting frequency of depressive feelings from 0 (least) to 3 (most). This was available in waves 1-5, 7, 8, and 10.

In the baseline analysis, we treated frequency of depressive feelings as continuous rather than ordinal to enable fixed effects models to be utilised. As such, we interpreted the variable as reflecting a continuum of frequency of depressive feelings (Posel *et al.*, 2021; Oyenubi and Kollamparambil, 2022). In a robustness tests, we defined an alternative binary dependent variable for moderate-to-high frequency of depressive feelings. This was equal to 1 if the individual reported a frequency score of 2 or 3 on the scale, and 0 otherwise. In a further robustness test, we instead treated frequency of depressive feelings as count data.

5.1.3.2 Smoking Status

Smoking status was elicited in the NIDS and NIDS-CRAM, albeit in different ways. In the NIDS, individuals were asked if they regularly smoke cigarettes, with those who say yes coded as smokers, and those who say no (either ex-smokers or those who have never smoked) as non-smokers. In the NIDS-CRAM, individuals were asked about their smoking behaviour in its third wave. Individuals were first asked smoked cigarettes in the week before lockdown (27 March 2020), *i.e.*, just before the tobacco sales ban. Given that this question referred to a period prior to the NIDS-CRAM data collection, it was assumed that the answer an individual would give had they been asked this in any other wave of the NIDS-CRAM would be the same. As such, the response given was interpolated to the first two waves of the NIDS-CRAM as these were collected during the stated time frame. Pre-ban smokers were also asked in wave 8 for the number of cigarettes they smoked in the past week, with those who stated a positive amount classified as post-ban smokers. This information was then combined with the NIDS smoking information to generate a binary variable indicative of smoking status for each wave of the data.

To test our second hypothesis that individuals who continued to smoke during the tobacco sales ban were more negatively impacted than those who stated they quit smoking, we subsequently differentiated between pre-ban smokers who continued or quit smoking during the ban. Individuals who stated they smoked in the week prior to lockdown were asked how many cigarettes they smoked on a typical day during lockdown, with those who stated they smoked a positive number of cigarettes classified as continuing smokers in the during ban waves of the data. Similarly, those who stated they did not smoke cigarettes during lockdown were classified as quitters. This variable was defined only for the ban waves, equalling zero in all pre- and post-ban waves.

5.1.3.3 Tobacco Sales Ban

Being interviewed during the tobacco sales ban was captured by a binary variable equal to 1 if the individual was interviewed between 27 March to 17 August 2020, and 0 otherwise. This duration coincided with the entirety of the first and second waves of the NIDS-CRAM. As frequency of depressive feelings was not elicited in the first NIDS-CRAM wave, only responses during the second wave of the NIDS-CRAM were captured by the indicator in the analysis. Thus, the indicator covered the interview period between 13 July to 8 August 2020 in the final month of the ban. Interviews for the third wave of the NIDS-CRAM commenced on 2 November 2020, approximately two-and-a-half months after the end of the tobacco sales ban. Since the ban was not re-introduced, individuals interviewed for the third, fourth, and fifth waves of the NIDS-CRAM represented post-ban observations (although the fourth wave was not used as frequency of depressive feelings was not observed), whilst all observations from the main NIDS dataset represented pre-ban observations. Table A1 in Appendix 2A summarises this timeline of the ban and NIDS-CRAM survey collection, alongside the corresponding 'Alert Level' in place.

5.1.3.4 Socioeconomic and Demographic Characteristics

The existing literature on the determinants of mental health in both South Africa (Tomita and Manuel, 2020; Hunt *et al.*, 2021; Posel *et al.*, 2021; Oyenubi *et al.*, 2022; Oyenubi and Kollamparambil, 2022) and wider contexts (Lund *et al.*, 2018; Huggard *et al.*, 2023) was used to select socioeconomic and demographic variables for the analysis. These included both individual- and household-level variables, as well as provincial and time variables. Table 5.1 provides details of how these were constructed with the data.

Individual-level variables included gender (female or male), race (Black African, Coloured, Asian/Indian, White), employment status (not economically active, unemployed, employed), highest level of educational attainment (from no schooling to tertiary education), and marital status (married or living with a partner versus not). Household-level variables include monthly household income per capita (*i.e.*, per household member), which was adjusted to May 2021 prices (the last month of observation) using the monthly Consumer Price Index (CPI) provided by Statistics South Africa[2]. Due to the skewness of income data, the natural logarithm was taken. Also included was receipt of a government grant by a household member in the past month (*e.g.*, a state old age pension or a child support grant), household size, and the geographical area type in which the

[2] Available from: https://www.statssa.gov.za/publications/P0141/CPIHistory.pdf?

household is located. Finally, provincial dummies were defined for each of South Africa's nine provinces, whilst dummy variables were also defined for month of interview and wave.

5.1.4 Data Cleaning and Sample Selection

Upon initial merging of the NIDS and NIDS-CRAM data there were 164,486 observations on individuals across ten waves of data. As the NIDS categorises individuals aged 15 years or older as adults, but the NIDS-CRAM only interviewed individuals aged 18 years or above, the sample was first restricted to those aged 18 years or above, removing 12,062 observations. This also ensured that all individuals in the sample were of the legal age to purchase tobacco in South Africa. Subsequently, we restricted the data to individuals without missing information for frequency of depressive feelings, removing 48,909 observations, of which 15,157 were from waves 6 and 9 when frequency of depressive feelings was not measured. Additionally, the 1% tails of the household income variable were winsorised to remove outliers to give a sample of 103,515 observations.

For the final analytical sample, we further excluded 11,135 singleton observations. Keeping singleton observations would overstate the statistical significance of the coefficients and may lead to incorrect inference (Correia, 2015). This figure largely reflected observations on individuals who only provided responses in one wave before dropping out of the sample. Indeed, there was a relatively high rate of attrition due to non-response between waves 1 and 2 of the NIDS (Mungai and Bayat, 2019). Finally, 6,422 missing observations on other variables included in the analysis provided unbalanced panel of consisting of 85,958 observations across 8 waves. Figure G1 in Appendix 2G presents a summary flowchart of the derivation of the analytical sample.

Given the relatively high rate of missing observations in the data, we explored the impact of missingness using independent sample *t* tests between those individuals included in the analytical sample and those excluded due to missing observations on one or more of the variables utilised in the baseline analytical models. Note that we excluded all observations from waves 6 and 9 of the data from these comparisons as these were not utilised in the analytical sample due to frequency of depressive feelings not being elicited in these waves. The results from this are provided in Table G1 in Appendix 2G.

Table G1 suggests that missingness in the sample was unlikely to be missing completely at random (MCAR), i.e., independent of the observed and unobserved data (Mack et al., 2018). Those included in the analytical sample tended to be less likely to report the lowest and highest frequencies of depressive symptoms compared to those missing from the analytical sample. On the other hand, smoking status did not significantly vary between the two samples. With regards to demographics, females were more prevalent in the analytical sample, as were those who were

either not economically active or in employment. The table further suggests that those with the lowest two or highest education level were less likely to have missing data compared to those with middle-level education. Individuals with a partner were also marginally more likely to be included in the analytical sample than those without. The most striking difference between the two samples was with regards to household income, with those excluded from the analytical sample having a mean household income approximately 1.7 times larger than those included. Those included in the sample were marginally more likely to have received a government grant, whilst the mean household size of the analytical sample was slightly smaller. Finally, the missing data was more prevalent amongst those residing in urban or farm geographical areas, and less prevalent amongst those residing in traditional areas. Thus, it is likely that missingness in our data is missing at random (MAR), given missingness appeared to be related to observable characteristics (Mack et al., 2018).

5.2 Descriptive Statistics

The following sub-section presents descriptive statistics for the characteristics of the sample of 85,958 observations utilised in the baseline analysis, followed by univariate statistics comparing differences in mean frequency of depressive symptoms between smokers and non-smokers across the whole sample, and then stratified by pre-, during-, and post-ban observations. Subsequently, a graphical depiction of mean frequency of depressive symptoms by wave is presented for smokers and non-smokers.

5.2.1 Baseline Sample

Most of the sample reported experiencing low frequencies of depressive feelings. The mean 'score' on the frequency of depressive symptoms scale was 0.627, indicating that on average individuals in the sample chose the 0 response on the scale. Looking at the distribution of responses on the scale, 56.2% chose 0 ("Rarely/Not at all"), 28.9% chose 1 ("Some of the time/Several days"), 10.8% chose 2 ("A moderate amount of the time/ more than half the days"), and 4.1% chose the 3 ("All of the time/Nearly every day").

For our baseline smoking variable, 'Smoker', 18.4% of individuals were identified as being smokers. Note that in the NIDS-CRAM, 13.7% of individuals identified themselves as pre-ban smokers, of which, 86.5% continued to smoke during the ban. For the post-ban period, 13.5% of the sample indicated they smoked after the ban, indicating that most of the smokers who stated they quit during the ban relapsed once it was lifted. This is consistent with findings from van Walbeek *et al.* (2023) on smoking, quitting, and relapse rates during and after the ban.

Turning to the socioeconomic and demographic characteristics, 61.2% of the sample were women, whilst most of the sample (82.8%) identified themselves as Black African, followed by Coloured

(13.2%), White (3.0%), and finally Asian/Indian (1.0%). It has been acknowledged by the NIDS authors that, relative to the general population, Black African and Coloured individuals were over-represented in the survey, whilst White and Asian/Indian were underrepresented (Brophy *et al*, 2018). This was due to the first wave achieving lower responses and higher rates of attrition from White and Indian areas. The top-up sample for wave 5 attempted to partially correct for this by interviewing wealthier individuals from all racial groups and thus increasing the number of White and Indian households in the sample (Brophy *et al.*, 2018).

The mean age of sample participants was approximately 41 years old. Most of the sample were employed, with 27.7% not economically active, and 27.6% unemployed. Thus, not accounting for those economically inactive, approximately 36.7% of individuals who wished to participate in the labour market were unemployed. This is relatively consistent with official statistics for the data collection period (April 2017 to May 2021), which show unemployment rates for the active labour force in South Africa rose from approximately 27.7% in the second quarter of 2017 (Statistics South Africa, 2017) to 34.4% by the second quarter of 2021 (Statistics South Africa, 2021a). Turning to education, 4.0% of the sample reported they have no formal schooling, whilst 14.9% of individuals' highest education level was equivalent to primary school (Grades 0 to 7), 10.4% equivalent to compulsory high school (Grades 8 and 9), 46.0% equivalent to National Qualification Framework (NQF) levels 2 to 4 (Grades 10 to 12 of high school and other vocational qualifications), and 24.7% had completed some form of tertiary education.

Regarding household compositions, 34.6% of individuals reported they were either married or living with a partner. This is close to an estimate from the South Africa Department of Social Development (2021) which indicated that 37.8% of household in South Africa were 'couple family' households in 2014. The report noted that the prevalence of such household was already low (54.7%) relative to the rest of the world in 1996 and has followed a steadily declining trend since. Indeed, declines in marriage rates in South Africa have been observed from at least 1960, particularly amongst Black-Africans (Posel and Rudwick, 2013). Various explanations for this are offered in the literature including gains in economic independence for women accompanied by declines in economic power for men, changes in perceptions of men making responsible husbands, declining ability of men to pay 'lobolo' (payment to a prospective bride's family), delinking of fertility with marriage and higher rates of pre-marital pregnancy, and societal and institutional changes in the post-apartheid period (Mhongo and Budlener, 2013).

The average household size in the sample was just over 5 household members, reflecting that approximately 33.6% of households in South Africa are 'extended households' comprising

multiple generations or relations (Statistics South Africa, 2021b). Indeed, examination of the data revealed that many households included unmarried adult children and/or both grandparent(s). Most household were in urban areas (62.3%), followed by 'traditional' areas (communally owned land under the jurisdiction of a traditional leader) (34.1%), and farm areas (land allocated for commercial farming including the structures and infrastructure on it) (3.6%). Mean total monthly household income per capita was approximately R1,268 (in May 2021 prices, equivalent to approximately 62 GBP in 2021 conversion rates). Note the low value of this figure reflects that it represented total household income per household member rather than per adult equivalent, and therefore does not account for different consumption needs of children or for economies of scale (Posel *et al.*, 2016). Finally, nearly 75% of individuals resided in a household which had received some form of government grant in the previous month.

5.2.2. Depressive Feelings by Smoking Status

Table 5.3 presents differences in frequencies of depressive feelings between smokers and non-smokers, stratified by the entire sample, and then by pre-, during-, and post-ban observations. Statistical significance in differences was tested using independent sample t-tests. For the whole sample, the mean frequency of depressive feelings score was higher for smokers than non-smokers, with a difference of 0.051 points (statistically significant at the 1% level). Examining the distribution of responses to each of the 4 levels indicates that differences between smokers and non-smokers were predominantly found between the lowest and highest two categories of depressive feelings, with 1.9 percentage points fewer smokers reporting a score of 0, and 1.2 and 1.0 percentage more smokers reporting a scores of 2 and 3 respectively. Thus, per expectations, smokers generally appeared to have poorer mental health than non-smokers (Tjora *et al.*, 2014; Liew and Gardner, 2016; Tomita and Manuel, 2020; Wooton *et al.*, 2020).

Examining the pre-ban statistics reveals that mean frequency of depressive feelings score was higher for smokers than non-smokers, although this difference of 0.042 point is lower compared to the whole sample. Smokers were 0.09 and 1.4 percentage points less likely to report the fewest two levels of depressive feelings respectively, and 1.1 percentage points more prevalent in the highest two categories. All differences were statistically significant. This suggests that in the pre-ban period, smoking status on significantly differentiated reported frequencies of depressive feelings.

The during ban statistics provide some preliminary evidence in favour of *H1*. The mean depressive feelings score for smokers was 0.133 points higher than for non-smokers, a difference that was over three times larger relative to pre-ban levels and highly statistically significant. Examining the

frequency categories indicates that this difference may have been largely driven by smokers being significantly less (more) likely to report the lowest (highest) frequency of depressive feelings relative to non-smokers. It is notable, and somewhat surprising, that the proportion of smokers and non-smokers reporting the lowest frequency of depressive feelings increased during this period, although the difference in prevalence in this category significantly widened from 0.9 to 5.4 percentage points. However, we also find that for both groups the proportions reporting the highest frequencies of depressive feelings significantly increased from 4.2% to 12.2% for smokers and from 3.1% to 8.8% for non-smokers, with the difference in prevalence between groups increasing by 2.3 percentage points.

Finally, the post-tobacco sales ban statistics indicate that depressive feelings score for both smokers and non-smokers rose, although the gap in score between the two groups narrowed by 0.027 points. This suggests a common factor to both groups may have caused depressive feelings to increase. Accompanying this, the proportion of smokers and non-smokers reporting the fewest levels of depressive feelings fell, but the difference between the groups remained almost identical. Consequently, we observe a rise in the proportion of both groups reporting the middle two frequency categories relative to during the ban, but a fall in those reporting the highest frequency level. Taken together, this suggests that in the post-ban period both groups were more likely to report mild to moderate frequencies of depressive feelings, whereas in the during ban period responses tended more towards the extremes. We discuss this the post-ban trend in more detail below.

5.2.3. Depressive Feelings by Smoking Status and Wave

Figure 5.1. presents a plot of the mean frequency of depressive feelings scores by wave for smokers and non-smokers. The graph indicates that in all waves, mean depressive feelings scores were higher for smokers than non-smokers, albeit this difference is very small in wave 1. Both groups followed a similar trend in mean scores over the five NIDS waves, although the gap in scores widened between waves 2 and 3. Mean depressive scores for non-smokers fell between waves 5 and 7, whilst for smokers an increase is observed. This period included the tobacco sales ban, which ended between waves 7 and 8. This tentatively suggests the ban may have had an impact on the mental health of smokers, however it must be noted that there is a three-year interval between the scores observed in wave 5 and the scores observed in wave 7, of which only approximately 5 months constituted the ban. Thus, it cannot be ruled out that other factors may explain this difference.

In wave 8, scores for both smokers and non-smokers increased. On the one hand, this is somewhat unexpected for smokers given the ban had been lifted by wave 8. However, since both groups follow a similar trend, this suggests that a common factor may have driven the increase in scores. This finding is also consistent with results from a previous study using NIDS-CRAM data for this period (Oyenubi and Kollamparambil, 2021; Ntuli and Kwenda, 2023). Mean scores for both groups then fell between waves 8 and 10, returning approximately to the last observed pre-ban values at wave 5.

It is possible that the evolution of the COVID-19 pandemic in late 2020 to mid-2021 can provide some explanation for this post-ban trend. Data collection for wave 8 took place between November and December 2020, during which fears of a 'second wave' of COVID-19 due to a more aggressive mutation of the virus were materialising as infection rates began to rapidly increase (Salyer *et al.*, 2021; Burger *et al.*, 2022). The roll-back of social security top-up and increased food price inflation during this period has also been cited as a possible explanation for this rise in frequency of depressive feelings between waves 7 and 8 (Oyenubi and Kollamparambil, 2021). Subsequently, the country was placed under tougher Alert Level 3 restrictions in response to this 'second wave' from 29 December 2020 to 28 February 2021, before being eased to Alert Level 1 from 1 March to 30 May 2021. Wave 10 data collection took place between 6 April and 11 May 2021. Thus, when interviewed, fears surrounding the virus were likely at their lowest point since the beginning of the pandemic, with the combination of increased vaccine availability (Burger *et al.*, 2022) and little-to-no restrictions meaning individuals were close to pre-pandemic conditions.

Overall, Figure 5.1 indicates that mean scores for both smokers and non-smokers generally followed similar trends over time. The notable difference was between waves 5 and 7, in which scores for smokers rose whilst scores for non-smokers fell. Given this coincided with the tobacco sales ban, this provides preliminary evidence that the ban may have had the hypothesised negative impact on the mental health of smokers. However, a simple comparison of means between smokers and non-smokers does not control for potential confounding variables, and thus an econometric analysis is required to confirm this relationship and ascertain possible causality.

6. Baseline Specifications and Estimation

This section first presents the baseline specifications for the models used to test the hypotheses specified in Section 4. This is followed by details of the estimation methods utilised for the baseline analysis and subsequent robustness checks.

6.1. Baseline Specifications

To study the impact of the tobacco sales ban on the mental health of smokers, we employed a difference-in-differences (DD) estimation strategy. Our treatment group was smokers, whilst our treatment was the ban. Our empirical strategy assumed that frequency of depressive feelings for smokers and non-smokers would have followed the same trajectory during the tobacco sales ban had the ban not been implemented (*i.e.*, the parallel trends assumption). This is a reasonable assumption given that other COVID-19 policy restrictions implemented in South Africa during this time applied to both smokers and non-smokers. Preliminary evidence for this was provided by Figure 5.1. in the preceding section. As discussed, this showed that whilst smokers consistently exhibited greater means levels of frequency of depressive feelings, both smokers and non-smokers followed similar trends between all waves except between wave 5 (the last pre-ban observation) and wave 7 (our during-ban observation) during which mean frequency of depressive feelings rose for smokers but fell for non-smokers. We conducted a more formal test of the parallel trends assumption by interacting smoking status with each wave. Details of this are provided in Section 6.2.

To test *H1,* we specified the following DD equation:

Equation (1)

$$FDF_{it} = \beta_1 Smoker_{it} + \beta_2 Ban_t + \beta_3 Smoker_{it} * Ban_t + \beta_4 \boldsymbol{X_{it}} + \nu_p + \nu_{1t} + \nu_{2t} + \mu_i + \varepsilon_{it}$$

Where *i* indexed the individual, *t* indexed the wave, and *p* indexed the province. FDF_{it} was our continuous dependent variable, frequency of depressive symptoms. Our treatment group consisted of pre-ban smokers, defined by the binary variable $Smoker_{it}$, and our treatment was the smoking ban, defined by the binary variable Ban_t. The DD interaction term was $Smoker_{it} * Ban_t$. $\boldsymbol{X_{it}}$ was the vector of individual- and household-level control variables detailed in Table 5.1, ν_p were province specific control dummies, ν_{1t} and ν_{2t} represented wave and month of interview controls, μ_i was the time-invariant individual-specific component of the error term, and ε_{it} was the time-varying individual error component. β_1 was expected to be positive given the well-established association between smoking and poorer mental health outcomes (Tjora *et al.*, 2014; Fluharty *et al.*, 2016; Liew and Gardner, 2016; Tomita and Manuel, 2020; Wooton *et al.*, 2020). β_2

was expected to be positive given we expected frequency of depressive feelings to be elevated during COVID-19 relative to pre-pandemic levels (Kim *et al.*, 2020; De Man *et al.*, 2022; Greyling *et al.*, 2021; Hunt *et al.*, 2021; Posel *et al.*, 2021; de la Rosa *et al.*, 2022; Oyenubi *et al.*, 2022; Rwafa-Ponela *et al.*, 2022; Oyenubi and Kollamparambil, 2022). As per *H1,* β_3 was expected to be positive, indicating frequency of depressive feelings were higher for smokers during the ban than non-smokers. The expected signs of the coefficients contained in β_4 on the controls in X_{it} are presented in Table 5.1. and were based upon findings from the existing literature on socioeconomic determinants of depression (Lund *et al.*, 2018; Huggard *et al.*, 2023) and studies conducting regression analyses of depression outcomes using NIDS and NIDS-CRAM data (Tomita and Manuel, 2020; Hunt *et al.*, 2021; Posel *et al.*, 2021; Oyenubi *et al.*, 2022; Oyenubi and Kollamparambil, 2022).

Specifically, we expected age to exhibit an inverted U-shaped relationship with frequency of depressive feelings, indicated by a positive coefficient on the age term and a negative coefficient on its square. Studies utilising NIDS and NIDS-CRAM data have consistently found the point estimates of age and it square in this direction, albeit statistical significance of the estimates has varied (Posel *et al.*, 2021; Oyenubi *et al.*, 2022; Oyenubi and Kollamparambil, 2022). Next, given 'Not Economically Active' is our omitted employment status variable, we expected the 'Employed' indicator to have a negative coefficient and the 'Unemployed' indicator to have a non-significant coefficient. Again, these expectations were based on point estimates from previous NIDS and NIDS-CRAM studies (Tomita and Manuel, 2020; Posel *et al.*, 2021). It is generally considered that education is negatively associated with depression (Lund *et al.*, 2018), however there is a suggestion from a systematic review of the literature this relationship may have reversed during the pandemic (Huggard *et al.*, 2023). Indeed, estimates for the effect of education on depression using NIDS data have found negative relationship (Dowdall *et al.*, 2017; Tomita and Manuel, 2020), whilst those using NIDS-CRAM data a positive but not significant effect of years of schooling on depression (Posel *et al.*, 2021; Oyenubi *et al.*, 2022; Oyenubi and Kollamparambil, 2022). Thus, for our analysis with 'No Schooling' omitted as the reference category, we tentatively expected each increasing level of education to exhibit an increasingly negative coefficient. However, given we had both pre- and during pandemic data, it may be that the point estimates obtained would be statistically insignificant. For marital status, we expected the coefficient on 'Married or Living with Partner' to be negative as this has been found with previous NIDS and NIDS-CRAM studies (Tomita and Manuel, 2020; Oyenubi *et al.*, 2022; Oyenubi and Kollamparambil, 2022).

At the household level, the coefficient on 'Log of Real Total Monthly Household Income Per Capita' was expected to be negative in line with previous findings from studies using NIDS and

NIDS-CRAM data (Tomita and Manuel, 2020; Hunt *et al.*, 2021; Posel *et al.*, 2021; Oyenubi *et al.*, 2022; Oyenubi and Kollamparambil, 2022). One study previously controlled for household size with NIDS-CRAM data, finding a positive (non-significant) coefficient when regressed on depression, thus we expected to find a similar relationship within our analyses (Oyenubi *et al.*, 2022). Finally, estimates for the relationship between geographical area type and depression have varied between studies using both the NIDS and NIDS-CRAM, although the majority of point estimates for the coefficients on residing in an 'Urban' area or a 'Farm' area relative to a 'Traditional' area have been positive but often not statistically significant (Tomita and Manuel, 2020; Posel *et al.*, 2021; Oyenubi *et al.*, 2022; Oyenubi and Kollamparambil, 2022).

We subsequently tested *H2* and *H3* using triple difference-in-differences (DDD) specifications. To test *H2*, which postulated that the impact of the tobacco sales ban on frequency of depressive symptoms would be greater for continuing smokers compared to those who have successfully quit smoking during the tobacco sales ban, we estimated the following equation:

Equation (2)

$$FDF_{it} = \beta_1 Smoker_{it} + \beta_2 Ban_t + \beta_3 Smoker_{it} * Ban_t + \beta_4 Smoker_{it} * Ban_t * Continuer_{it} + \boldsymbol{\beta_5 X_{it}} + \nu_p + \nu_{1t} + \nu_{2t} + \mu_i + \varepsilon_{it}$$

Where $Continuer_{it}$ was a binary variable equal to one if the individual was a pre-ban smoker who reporting continuing smoking during the ban, and 0 otherwise. Note we did not include this a stand-alone variable as it only differentiated between smokers during the ban period. As before, we expected β_1 and β_2, to be positive. The DD coefficient β_3 was also expected to be positive, representing the effect of the ban on pre-ban smokers (both continuers and quitters), with β_4 representing the estimated heterogeneous DDD estimate for the effect of the ban on continuing smokers. As per *H2*, this was expected to be positive.

To test *H3,* which postulated that the impact of the tobacco sales ban on frequency of depressive symptoms will be greater for female smokers than male smokers, we estimated the following DDD model specified by *Equation (3)*.

Equation (3)

$$FDF_{it} = \beta_1 Smoker_{it} + \beta_2 Ban_t + \beta_3 Smoker_{it} * Ban_t + \beta_4 Smoker_{it} * Female_i + \beta_5 Smoker_{it} * Ban_t * Female_i + \beta_6 \boldsymbol{X_{it}} + \nu_p + \nu_{1t} + \nu_{2t} + \mu_i + \varepsilon_{it}$$

Where $Female_{it}$ was a binary variable equal to 1 if the individual is female. Note that this was not included as an individual variable in the model as gender is time-invariant. β_4 provided the estimated for the relationship between smoking and frequency of depressive feelings for women

compared to men and was expected to not significantly differ from zero given that no clear pattern in the relationship between smoking and mental health outcomes has been established in the literature (Fluharty *et al.*, 2016). β_3 provided the DD estimate for the effect of the tobacco sales ban on frequency of depressive feelings for men, whilst β_5 provided the heterogeneous DDD estimate for the effect of the tobacco sales ban on frequency of depressive feelings for women. As per *H3*, both β_3 and β_5 were expected to be positive but with the magnitude of the latter being greater than the former.

6.2. Estimation Methods

6.2.1 Baseline Analysis

In the baseline analysis testing *H1, H2,* and *H3*, we treated frequency of depressive feelings as a continuous variable to allow for the use of linear fixed effects estimation. This is advantageous as the fixed effects estimations controls for unobserved individual-level time invariant heterogeneity. Conversely, the fixed effects estimator cannot be used with ordinal outcome models due to the incidental parameters problem (Greene, 2004). The disadvantage of this approach is that the estimated coefficients are less informative than if we were to utilise an ordinal estimator to obtain average marginal effects. We interpret the estimated coefficients as the associated change in score along a hypothetical (bounded) continuum of frequency of depressive feelings. We believed that the advantages of controlling for individual level fixed effects outweighed the drawbacks, given that failure to account for these can lead to biased coefficients due to the potentially confounding effect of unobserved time-invariant individual-level covariates of mental health and smoking such as genetics. All analysis was conducted in Stata 17 (StataCorp, 2021).

Using this estimation strategy, we first conducted a formal test of the parallel trends assumption by estimating *Equation (1)* with the inclusion of interaction terms between smoking status and each wave of observation. For the parallel trends assumption to hold, the coefficients on all pre- and post-ban interactions should not be statistically significant. The results from estimating this model are provided in column 1 of Table C1 and depicted graphically in Figure C1 in Appendix 2C. The results suggested that the parallel trends assumption may not hold as our estimated coefficients on the wave 3 and wave 4 interaction terms with smoking status were positive and statistically significant.

One method to address this violation of the parallel trends assumption is the entropy-balancing approach[3] proposed by Hainmueller (2012). This is a data pre-processing method to create balanced samples between a treatment and control group, allowing for subsequent estimation of treatment effects. Entropy balancing was conducted in two steps. First, a set of balance constraints on the first and second moments of the covariates contained in vector $\boldsymbol{X_{it}}$ were imposed. Entropy balancing then directly adjusted unit weights to these sample moments, ensuring that the reweighted non-smoker group matched almost exactly to the smoker group on these sample moments. The intuition behind this approach is that it can effectively ensure the observable characteristics of smokers and non-smokers were as similar as possible, mimicking a randomised controlled experiment (Neuenkirch and Neumeier, 2016). The efficacy of the approach in balancing a sample is displayed in Table D1 in Appendix 2D, showing the first and second moments of our covariates matched near-identically between smokers and non-smokers following entropy balancing. The second step then utilised these estimated weights in the linear fixed effects models. This produced an estimate of the average treatment effect of the tobacco sales ban on frequency of depressive feelings amongst smokers.

Entropy balancing has several advantages over other matching methods, such as propensity score matching (Hainmueller,2012). From the perspective of this analysis, the major advantage was that the full sample for the regression analysis on the matched sample was retained. Conversely, propensity score matching would have discarded a significant proportion of the control sample of non-smokers. Given the relatively small window in which the treatment (the tobacco sales ban) applied to the treated group (smokers), discarding a high number of control observations (non-smokers) would have significantly reduced the statistical power of the model. Furthermore, if only a sub-set of units from the full control group were utilised, this may have caused an insufficient balance of pre-treatment characteristics between the treatment and control group, thereby leading to biased estimates of the treatment effect (Neuenkirch and Neumeier, 2016).

We subsequently re-ran our regression model testing the parallel trends assumption using the entropy balanced weights. The results are provided in column 2 of Table C1 and Figure C2 in

[3] This was implemented in Stata using the user-written package *ebalance* (Hainmueller and Xu, 2013). Further details on the entropy balancing approach are provided in Hainmueller's (2012) paper, including the mathematical derivations of the weighting procedure and evidence from Monte Carlo simulations that it exhibits desirable finite sample properties.

Appendix 2C. These indicated that the parallel trends assumption held in our reweighted sample, as none of the coefficient on the pre-ban interaction terms were statistically significant.

Considering this, we estimated *Equations (1-3)* using both the unweighted sample and the entropy balanced sample. We employed the user-written *reghdfe* package (Correia, 2014) in Stata 17 which allowed entropy weights to be included in a linear fixed effects model. The package also automatically dropped singleton observations as including such observations within linear regressions can overstate statistical significance and lead to incorrect inference (Correia, 2015). For all models, we estimated cluster-robust standard errors clustered at the individual level.

6.2.2 Robustness Checks

We conducted three robustness checks for our baseline results. We firstly utilised alternative estimation methods to address the assumption of treating frequency of depressive feelings as a continuous variable. We then partially addressed the issue of possible endogeneity between smoking and depressive feelings through an adapted incident cohort approach. We conducted all robustness checks using entropy balanced samples given the evidence that the parallel trends assumption may be violated with the unweighted data.

6.2.2.1 Linear Probability Models

For our first robustness check, we defined a binary outcome variable for moderate or high frequency of depressive feelings equal to 1 if the individual reports a frequency score of 2 or more. We then re-estimated *Equations (1-3)* using linear probability models with fixed effects with the entropy balanced baseline sample. One advantage of this is that it provided a more natural interpretation to the estimate treatment effects as the coefficients represent the change in probability of reporting moderate-to-high frequencies of depressive feelings. We decided this approach was preferable over utilising ordinal estimation to enhance the interpretation of our models since we were not restricted by the incidental parameters problem and could still utilise estimation commands compatible with entropy weights. The estimated coefficients were then interpreted as representing the probability of an individual reporting moderate-to-high frequency of depressive feelings.

6.2.2.2 Count Data Models

For our second robustness check, we treated frequency of depressive feelings as count data rather than a continuous variable. This provided us with a choice of two estimation methods, Poisson or negative binomial regression. Our preferred method for re-estimating *Equations (1-3)* was to use Poisson regression, since entropy weights cannot currently be incorporated into the negative

binomial models with currently available Stata estimation commands. As such, we utilised the user-written *ppmlhdfe* command (Correia *et al.*, 2019), which is a non-linear the equivalent to the *reghdfe* command utilised for the baseline analysis. Alongside removing singletons, the command also dropped observations which were separated. In our case, this removed individuals who only reported zero depressive feelings in all observed waves. As this inherently changed our sample composition[4], we calculated new entropy weights when conducting the entropy balanced Poisson regression. For interpretation, the coefficients obtained in the Poisson model were exponentiated to represent the multiplicative change in the rate of frequency of depressive feelings associated with a one-unit change in the regressors, *i.e.*, the incidence-ratio rate.

6.2.2.3 History of Depression

Evidence from the literature suggests that individuals with depression may smoke more than non-depressed individuals (Tjora *et al.*, 2014; Liew and Gardner, 2016; Wooton *et al.*, 2020). This may have led to a potential endogeneity issue between smoking and frequency of depressive feelings in our models. To partially address this, we adapted the incident cohort approach implemented by Tomita and Manuel (2020) using information from all ten questions on the CESD-10 administered in the NIDS to define a binary variable equal to one for likely clinical depression based on the accepted threshold score of 10 (Andersen *et al.*, 1994). We then firstly removed all individuals who exhibited a 'strong history' of depressive symptoms by scoring 10 or more on the CESD-10 in all NIDS waves. We then alternatively restricted the sample to individuals without a 'recent history' of depressive symptoms, by removing individuals who scored 10 or more on the CESD-10 in the final pre-ban NIDS wave. *Equations (1-3)* were then re-estimated through linear fixed effects regression both with newly constructed entropy balance weights to reflect this change in sample composition.

6.2.2.4 Ex-Smokers

Finally, some of the existing literature suggests that ex-smokers and those who have never smoked in their lifetime may have a different propensity to smoke. Hinks and Katasaros (2012) outlined that ex-smokers differ from never smokers in the sense that never smokers exhibit a clear propensity not to smoke, whilst many ex-smokers may intrinsically prefer to smoke but choose not to, perhaps through their understanding of the long-term health consequences from smoking.

[4] We also perform a 'robustness check of this robustness check' to explore whether this removal of individuals who have never reported more than 0 frequency of depressive feelings impacts our baseline results with linear regression models on our new sub-sample. Results of this are available in Table F3 in Appendix 1F.

As such, ex-smokers and never smokers may be heterogeneous in their behaviour and attitudes towards the ban. We therefore first re-estimated our baseline models testing H1, H2, and H3 excluding ex-smokers from the sample. We defined ex-smokers as individuals who either self-reported being ex-smokers when asked in the NIDS, or individuals who had previously stated they were smokers but in a subsequent wave stated they were not smokers. Subsequently, we replaced our binary smoking status variable with a categorical variable representing 'Never Smokers' (=0), 'Ex-Smokers' (=1), and 'Current Smokers' (=2) and re-estimated our models testing H1 and H3. We could not test H2 here as by definition ex-smokers would also include post-ban quitters. Our expectation is that the mental health of ex-smokers may be positively influenced by the ban if they see it as affirmation for their previous decision to quit smoking.

7. Results

This section presents and discusses the results from our analyses. First reported are the results from our baseline analysis testing our three hypotheses. Subsequently we report the results from the four robustness checks.

7.1 Baseline Analysis

The results of our baseline analysis testing the three hypotheses stated in in Section 4 are presented in Tables 7.1, 7.2, and 7.3 respectively. All models were estimated using linear fixed effects estimation on both the unweighted and entropy balanced samples. The estimated coefficients for the control variables are only presented and discussed for the model testing *H1* for the sake of brevity, with full results for the models which tested *H2* and *H3* provided in Tables E1 and E2 in Appendix 2E.

7.1.1 Smokers and the Tobacco Sales Ban

Table 7.1 provides the results of our baseline model which tested *H1* through estimating *Equation (1)*. The first column provides the results using the unweighted sample. In line with expectations, being a smoker was positively associated with frequency of depressive feelings. This is concurrent with the literature on the relationship between smoking and depression (Tjora *et al.*, 2014; Fluharty *et al.*, 2016; Liew and Gardner, 2016; Tomita and Manuel, 2020; Wooton *et al.*, 2020). The estimated coefficient indicates smoking was associated with a 0.066-point increase in frequency of depressive feelings. Being interviewed during the tobacco sales ban period, ceteris paribus, was not significantly associated with frequency of depressive feelings. This implies that the average frequency of depressive feelings in the sample during the ban (*i.e.*, wave 7) did not significantly differ from wave 1. This is somewhat surprising given the expectation that frequency of depressive feelings would be higher during COVID-19 relative to their pre-pandemic level. However, it is important to remember that our ban indicator represented data collection at wave 7, which was conducted in July and August 2020 in a period where COVID-19 cases had fallen from the initial levels in the first few months of the pandemic and restrictions had been lowered to Alert Level 3 in June 2020, granting South Africans considerably more freedoms than previously experienced since the beginning of the pandemic. Finally, we found no evidence for *H1*, with the coefficient on the DD interaction term between being a smoker and being interviewed during the ban positive but not statistically significant. Before considering reasons for this finding, we first discuss the results using the entropy balanced sample.

In Section 6.1, we found evidence that the parallel trends assumption required for DD analysis may not hold. However, we further demonstrated that employing entropy balancing led to the

parallel trends assumption holding. Column 2 of Table 7.1 provides the results from estimating *Equation (1)* using the entropy balance weights. Consistent with the unweighted model, we found smoking was positively associated with frequency of depressive feelings, whilst the coefficients on the ban indicator and the DD term remained non-significant. Thus, both models provided no evidence for our first hypothesis.

It is plausible this lack of a statistically significant effect of the ban on smokers' frequency of depressive feelings may have reflected that the ban had already been in place for approximately three months by the time of interview. Thus, pre-ban smokers may have adapted to life under the ban to some extent. Some smokers may have successfully quit in the preceding months, meaning the initial psychological effects associated with nicotine withdrawal would likely have subsided. Those who continued to smoke may have established sufficient, albeit illicit, supply lines to negate potential withdrawal symptoms and alleviate concerns over restricted access to a potential coping mechanism. However, most of the postulated mechanisms linking the ban to continuing smokers' mental health outlined in Section 4 remain valid, meriting the further analysis which distinguished between continuing smokers and those who quit during the ban.

Turning now to the control variables in the unweighted model, we generally found the expected relationships with frequency of depressive feelings outlined in Table 5.1., or non-significant relationships with frequency of depressive feelings. No variables exhibited a converse relationship to expectations. The point estimates on age and its square indicated the expected inverted U-shaped relationship with frequency of depressive feelings, however the positive coefficient on age was not statistically significant. This is consistent with previous findings from a study using the NIDS and NIDS-CRAM data (Posel *et al.*, 2021). Next, we found that individuals who were unemployed or employed reported fewer depressive feelings than those who were not economically active, with the magnitude of the estimated coefficient for those in employment more than double that for the unemployed. Regarding the finding for employment, this was consistent with expectations given the well-established links between employment and mental health (Lund *et al.*, 2018), which have been shown to be particularly important in the context of employment uncertainty during the pandemic in South Africa (Posel *et al.*, 2021; Oyenubi and Kollamparambil, 2022). We expected the coefficient on unemployed to not significantly differ from zero, however this result implies that the unemployed fared slightly better than those not economically active.

Somewhat surprisingly, we failed to find a negative relationship between increasing education levels and frequency of depressive feelings as is often suggested by the literature on determinants

of mental health (Lund *et al.*, 2018). However, this was consistent with studies utilising NIDS-CRAM data which found increasing education levels to not significantly predict depression scores (Tomita and Manuel, 2020; Posel *et al.*, 2021; Oyenubi *et al.*, 2022; Oyenubi and Kollamparambil, 2022). Furthermore, there are suggestions from the literature that whilst lower educational levels in pre-pandemic times often predict poorer mental health, it was those with higher education who were more at risk of mental illness during the pandemic (Huggard *et al.*, 2023). Since we had data both before and during the pandemic, our findings of non-significant coefficients on education may reflect these competing forces cancelling out. Next, we found the expected statistically significant negative relationship between living with a partner and depressive feelings. This is largely consistent with findings from studies using just NIDS data (Dowdall *et al.*, 2017; Tomita and Manuel, 2020) or just NIDS-CRAM data (Oyenubi and Kollamparambil, 2022).

Turning to household-level control variables, as expected, frequency of depressive feelings decreased with household income per capita. This is consistent with findings from previous studies using both NIDS and NIDS-CRAM data (Tomita and Manuel, 2020; Hunt *et al.*, 2021l Posel *et al.*, 2021). The estimated coefficient implies a 100% increase in household income per capita reduced frequency of depressive feelings score by approximately 0.028-points. Receipt of a government grant within a household was also negatively associated with frequency of depressive feelings. Again, this is unsurprising given the existing evidence for the impact government support may have on relieving depressive symptoms (Tomita and Manuel, 2020), particularly in the context of the pandemic (Posel *et al.*, 2021). Finally, we did not find depressive symptoms to be predicted by living in an urban or farm area relative to a rural area, nor by household size.

The results pertaining to the control variables were generally consistent in the entropy balanced model displayed in column 2.

7.1.2 Continuing Smokers vs Quitters

Table 7.2 provides the results from estimating *Equation (2)* to test *H2*, in which we differentiated between pre-ban smokers who stated they did and did not continue smoking cigarettes during the ban. The model was estimated using the unweighted (column 1) and the entropy balanced (column 2) samples.

Columns 1 and 2 of Table 7.2 show consistent estimates in the sign and statistical significance of the key coefficients of interest. As expected, we found a statistically significant positive relationship between being a smoker and frequency of depressive feelings. The estimated coefficients on the ban indicator and its interaction with smoking status were not statistically significant, however it is notable that the point estimates changed from positive to negative after introducing our triple

interaction term. Concurrent with *H2*, we found a positive coefficient on the DDD interaction term between smoking, the ban, and our continuing smoker variable, albeit this was only weakly significant at the 10% level. This implies that at this point of the ban, it was only those pre-ban smokers who continued to smoke during the ban who exhibited greater frequencies of depressive feelings.

Taken together, the results in Table 7.2 suggest that the non-significant estimated effect of the ban on smokers' mental health found in Table 7.1 was due to a differential effect of the ban on those who continued to smoke and those who successfully quit. Indeed, the size of the point DDD estimate was more than four times larger than that obtained when we did not differentiate between continuers and quitters in Table 7.1. Notably, we now also observed that the DD point estimate for the interaction term between smoking and the ban was negative (but not statistically significant). This suggests that quitters may have been supressing our estimated effect of the ban when we failed to differentiate between them and continuing smokers in our first model.

We can first explain this result through the timing of interviews during the ban, which took place approximately 3 months after the ban was first implemented. It is reasonable to assume that whilst quitters may have initially suffered ill mental health from nicotine withdrawal, anger towards the ban, and restricted access to a potential coping mechanism for stressors incurred by the pandemic, these factors would likely have waned over time as their addiction receded and the implications of the ban no longer applied to them. Indeed, the negative point-estimate for the effect of the ban on quitters suggests that the ban may even at this stage have positively impacted quitters' mental health as a result of successful cessation. This may reflect that for those who successfully quit, the ban acted as an effective commitment device (Odermatt and Stutzer, 2015; Leicester and Levell, 2016; Yang and Zucchelli, 2018). However, we cannot definitively conclude this as the estimate was not statistically significant, which may partially be a result of the low quit rate during the ban of 14.5% meaning we observed a relatively small number of quitters in our estimation sample leading to large standard errors.

There is more confidence in the result that those who continued smoking during the ban exhibited greater frequencies of depressive feelings. The estimated DD coefficients imply the 'treatment' effect of the ban was equivalent to a 0.237- to 0.243-point higher score in depressive feelings for continuing smokers. This implies the effect for continuing smokers was equivalent to increasing depressive feelings score by approximately 1.39 times the sample mean pre-ban level of 0.631 points. This was the largest estimated effect of all variables in our model, including traditional determinants of mental health such as being employed (reduces score by 0.066 points) or

cohabiting with a partner (reduces score by 0.049 points). Indeed, the size of the estimate suggests the effect was equivalent to approximate six-fold reduction in household income per capita[5], although we should attribute caution this given the relative difference in statistical certainty between the two coefficients.

As postulated in Section 4, this finding could be for several reasons. Smokers exhibited significant anger and animosity towards the start of the ban (van Walbeek *et al.*, 2020), and these feelings would likely only have intensified amongst those who continued to smoke as the ban continued for several months despite other restrictions being eased during the period, including the ending of prohibition on the sale of alcohol. This would likely drive a significant sense of injustice amongst many smokers at what they may perceive as an unjustified and unfairly targeted policy infringing on their personal rights and freedoms. Indeed, Hinks and Katsaros (2012) use this explanation of threat to individuals' personal liberties for their results from smokers in the BHPS exhibiting poorer wellbeing immediately after the implementation of a ban on smoking in public places (which was clearly less stringent than that imposed on South African smokers). Second, it is likely that the struggling quitters hypothesis (SQH), which posits that failed cessation attempts negatively impact smokers' mental health (Berlin *et al.*, 2010; McDermott *et al.*, 2013; Capron *et al.*, 2014, Kim *et al.*, 2019), may be playing an important role. Indeed, estimates from the first REEP survey conducted between 29 April and May 2020 indicated that 41% of smokers stated they had attempted to quit, but by the time of the second REEP survey conducted in June 2020 only 9% had been successful (van der Zee *et al.*, 2023). Third, by the time of interview, all continuing smokers would almost certainly have run out of any pre-ban stocks of cigarettes. Thus, cigarettes would have mostly been sourced from the illicit market. Not only may this affect mental health due to fears of negative societal perceptions due to breaking COVID-19 restrictions (Berrocal *et al.*, 2021; Bor *et al.*, 2023), but smokers also faced hyperinflated prices at a time of significant income and employment uncertainty (Posel *et al.*, 2021; Ohrnberger, 2022; Oyenubi and Kollamparambil, 2022), possibly inducing negative psychological feelings due to the increased opportunity cost to smoking.

[5] The estimated coefficient on log of real household income per capita was 0.045 (95% CI -0.063 to -0.028), implying a 100% increase is equivalent to a 0.045-point reduction in frequency of depressive feelings score. Thus, a sixfold decrease in household income per capita would increase frequency of depressive feelings score by approximately 0.225 points. See Table E1 in Appendix 2E for these results in full.

7.1.3 Female vs Male Smokers

It is possible that heterogeneity in the effect of the ban on smokers' mental health between men and women may also explain our non-significant estimated effect of the ban shown in Table 7.1. In *H3*, we postulated that female smokers would be more affected than male smokers by the ban. The results from estimating *Equation (3)* to test this hypothesis are presented in Table 7.3. In this model, we included a triple interaction term between smoking, the tobacco sales ban, and an indicator for being female. Again, we utilised both the unweighted and the entropy balanced samples to estimate linear fixed effects regression models.

Firstly, in both models we found smoking was significantly associated with higher depressive feelings, whilst its interaction term with female was negative but not statistically significant. This is consistent with findings from a systematic review of the relationship between smoking and mental health, which indicated there are no consistent patterns in the effect of smoking on mental health between genders (Hughes, 2007). The estimated coefficient for the ban remained non-statistically significant, however in the unweighted model we find a negative and statistically significant coefficient on its interaction term with female. However, this dissipated in the entropy balanced sample.

Finally, we found that the interaction term between smoking and the ban was not statistically significant, however, when further interacted with the female indicator we found a large and strongly significant positive coefficient which was almost identical in both the unweighted and entropy balanced models. The estimate for the entropy balanced sample indicates the effect of the ban on female smokers' was to increase frequency of depressive feelings by 0.395-points. This implies the effect of the ban on female smokers was equivalent to increasing depressive feelings score by approximately 1.62 times the sample mean pre-ban score of 0.631 points. The magnitude of this effect was significantly larger than the estimated coefficients on any of the other variables in the model. Conversely, male smokers' depressive feelings were not significantly affected by the ban. These findings provide partial support to *H3*, as we hypothesised that both male and female smokers would be impacted by the ban, but females to a greater extent. Regardless, our reasons for postulating that female smokers would be more affected than male smokers remain.

Firstly, women have been found to have poorer rates of successful cessation (Ward *et al.*, 1997; Smith *et al.*, 2016), be more likely to continue smoking following adverse life events (McKee *et al.*, 2003), and more reliant on social support for successful cessation attempts (Westmaas and Langsam, 2005). These latter two points are particularly relevant in the context of the pandemic, which like induced a negative financial shock for many South Africans, whilst restrictions limited

opportunities for social support. Indeed, examining quit rates in our estimation sample indicated that approximately 14% of females were identified as quitters compared to 16% of male smokers. Thus, women may have been more likely to continue smoking than men, and thus more likely to experience the potential mechanisms linking continued smoking to poorer mental health. One such mechanism of concern is the SQH, as some evidence suggests women to be more susceptible to negative mental health affects following relapse (Kim *et al.*, 2019).

Women also tend to report smoking as a coping mechanism to deal with stress and reduce negative affect (Livson and Leino, 1988; Zuckerman *et al.*, 1990 Brandon and Baker, 1991; Berlin *et al.*, 2003; Fidler and West, 2009; Pang *et al.*, 2014). This finding has been reported to be held even by women who have quit smoking (Fidler and West, 2009). Thus, even the small proportion of women who quit during the ban may still perceive the ban to have denied them a mechanism to cope with the stressors of the pandemic. For those continuing to smoke, we may expect the ban to still have impacted on utilisation of cigarettes as a coping mechanism. Cigarette consumption during the ban fell from 7.9 cigarettes to 6.5 cigarettes per day during the ban (van Walbeek *et al.*, 2022), whilst in our data, the most prevalent package size for cigarettes during the ban was a single stick (52.9%) whereas in the pre-ban wave a packet of 20 was the most prevalent package size (39.73%). Given evidence that in response to induced negative mood that women are more likely to report craving a cigarette and are quicker to choose to do so (Perkins *et al.*, 2013; Weinberger and McKee, 2012), it is plausible that women during the ban were not as easily able to access cigarettes on demand in response to stressors.

7.2 Robustness Checks

The results from the three robustness checks of our baseline results are presented and discussed below. Given the evidence that the parallel trends assumption may not hold without entropy balancing, we only conducted these robustness tests with entropy balanced samples for brevity. Where the sample composition changes, new entropy weights are first estimated. Tables 7.4 to 7.6 provide the results from each robustness check, with the coefficients on the control variables omitted for brevity. Full results for the estimated models are available in Tables F1, F2, and F4 in Appendix 2F.

7.2.1. Robustness Check 1 – Linear Probability Model

For the first robustness check, we re-estimated our baseline models with a new binary dependent variable for reporting moderate-to-high frequencies of depressive feelings (*i.e.*, a score of 2 or 3 on the ordinal scale). The models were estimated using linear probability models with fixed effects.

Our estimation sample did not change from the baseline sample, with 85,958 observations on individuals utilised. The results are presented in Table 7.4.

Panel A provides the results from the robustness test of our baseline results for *H1*. Consistent with our baseline estimation, we did not find a statistically significant DD estimate for the effect of the ban on smokers' frequency of depressive feelings. Panel B provides the results from the robustness test of our baseline results for *H2*. Consistent with the baseline estimation, we found a statistically significant positive coefficient only on the triple interaction term. The DDD estimate indicates that effect of the ban on continuer smokers was to increase the probability of them reporting moderate-to-high depressive feelings by 10.7 percentage points. Finally, Panel C indicates our baseline results for testing *H3* were also robust to this alternative outcome specification. We find the triple interaction term between smoking, the ban, and female was positive and statistically significant, albeit only at the 10% level. The estimated coefficient implies that the DDD estimated effect of the ban on female smokers was to increase their probability of reporting moderate-to-high depressive feelings by 10.1 percentage points. Conversely, the ban did not have a significant effect on the probability of reporting moderate-to-high depressive feelings for male smokers. Consistent with our baseline findings, in Panels B and C, the estimated effect of the ban on continuing smokers and female smokers was largest predictor of depressive feelings found in our model, significantly outweighing the estimates for employment, marital status, household income, and receipt of government grants.

Thus, our baseline findings were robust to this alternative specification using a binary variable for moderate-to-high depressive feelings and utilising linear probability model estimation.

7.2.2 Robustness Check 2 – Count Models

For our second robustness check, we treated frequency of depressive feelings as count data (taking the values of 0 to 3) and re-estimated our baseline models using Poisson regression with fixed effects. Alongside dropping singleton observations from the model, Poisson regression also drops observations which are separated. This removed, 11,859 observations, consisting of individuals who reported 0 depressive feelings in all waves in which they were observed.[6] Thus, our estimation

[6] We also check the effect of this change in sample composition with our baseline linear estimation method (see Table F3 in Appendix 2F for the presentation and brief discussion of these results). This shows that on the sub-sample of individuals used in the Poisson regression, our baseline DID estimates very marginally increase. This suggests that the robustness of the results between treating frequency of depressive feelings as continuous and count data were not primarily the result of removing these individuals.

sample consisted of 74,099 observations on individuals, and as such, we re-estimated new entropy weights to reflect this change in sample composition. The results are provided in Table 7.5. We report the exponentiated coefficients, which give the incidence-rate ratio (IRR) associated with each regressor, for ease of interpretation.

Firstly, Panel A of Table 7.5 indicates our baseline results were robust to this alternative estimation strategy. We found smoking was positively associated with frequency of depressive feelings, with the IRR indicating the expected rate of frequency of depressive feelings increased by 1.115 times for smokers compared to non-smokers. As found in the baseline analysis, neither the ban nor its interaction with smoking status significantly affected the rate of frequency of depressive feelings. Panel B also indicates our baseline results for *H2* were robust under Poisson estimation. Focussing on the DDD estimate, the results imply the rate of frequency of depressive feelings was increased by 1.434 times for continuing smokers, whilst the rate for pre-ban smokers who quit, and non-smokers was not significantly affected by the ban. Panel C indicates our DDD results for *H3* from the baseline analysis were robust to Poisson estimation. As before, we found that the ban only significantly affected the frequency of depressive feelings exhibited by female smokers. The IRR estimate indicates the rate of frequency of depressive feelings was increased by female smokers during the ban by 1.685 times. One difference from our previous baseline model and the linear probability model for moderate-to-high frequency of depressive feelings was that the interaction term between smoker and female was now statistically significant at the 10% level. Taken together with the IRR estimate on the smoking indicator, this implies that male smokers exhibited an increased rate of frequency of depressive feelings by 1.133 times, however for female smokers this rate was reduced by 0.919 times, suggesting that whilst overall female smokers still exhibited a higher rate of depressive feelings than non-smokers, this effect was significantly lower compared to their male counterparts.

7.2.3 Robustness Check 3: History of Depressive Symptoms

For our third robustness check, we examined the impact of removing individuals with a history of significant depressive symptoms in the pre-ban waves. This was an adaptation of the incident cohort approach utilised by Tomita and Manuel (2020) to help reduce the possibility of endogeneity between smoking and depressive feelings. We based this on responses provided to the full CESD-10 instrument administered in the NIDS, for which a summed score of 10 or more

can be taken as being indicative of significant depressive symptoms[7]. We utilised this information in two ways. Firstly, we dropped individuals with a strong history of depressive symptoms whereby they scored 10 or more on the CESD-10 in all waves of the NIDS. Second, we dropped individuals with a recent history of depressive symptoms, whereby they scored 10 or more on the CESD-10 scale in wave 5 (*i.e.*, the last pre-ban wave). As with our second robustness check, this changed our sample composition, therefore we re-estimated entropy weights before estimating our models. The results are provided in Table 7.6. Our sample without individuals with a strong history of significant depressive symptoms consisted of 80,139 observations, whilst our sample without individuals with a recent history of significant depressive symptoms consisted of 81,087 observations. The results are presented in adjacent columns for each panel of the table.

Panel A indicates that our baseline results for *H1* were robust to exclusion of individuals with a strong or recent history of significant depressive symptoms. The estimated coefficient on smoking in both models was only marginally lower than that obtained in the baseline analysis (0.065). This indicates that smoking still exhibited a strong positive relationship with depressive feelings even when individuals with a history of depressive symptoms are removed from the sample, and thus reverse causality is unlikely to be driving this relationship. As in the baseline analysis, the ban and its interaction term were not significantly related to frequency of depressive feelings.

For both columns in Panel B, we find the DDD interaction term was smaller than the baseline model (0.243) and not quite statistically significant at the 10% level. We postulated that one of the key mechanisms driving the effect of the ban on continuing smokers' depressive feelings may be the SQH, positing that individuals who relapse from cessation attempts may suffer negative psychological consequences. Some findings from the literature suggests this effect may be stronger amongst those with a history of mental illness (Berlin *et al.*, 2010; Capron *et al.*, 2014). As such, this reduction in effect was not necessarily surprising.

Finally, both columns of Panel C show our estimated effect of the ban on female smokers was robust to exclusion of individuals with a strong or recent history of significant depressive symptoms. As was the case with Panel B, the DDD estimate was slightly reduced from the baseline model, however in this instance statistical significance was unaffected. The remaining estimated coefficients were also consistent with our baseline model.

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[7] A score of 10 or more is generally utilised in the existing literature to be indicative of clinically significant symptoms of depression on the CESD-10 scale (Andersen *et al.*, 1994).

Overall, the robustness check suggests that continuing and female smokers with a history of depressive symptoms may have been slightly more affected by the ban than those without. In the case of continuing smokers, this difference was enough to reduce the DDD estimate to a non-significant level, albeit only just.

7.2.4 Robustness Check 4: Ex-Smokers

For our final robustness check, we examined the impact of differentiating ex-smokers from never smokers in our model. This may be an important distinction since ex-smokers and never smokers are likely to have different propensities to smoke, and therefore may react to the ban differently. In particular, whilst the ban may have no relevance to never smokers, ex-smokers may view the implementation of the ban as affirmation for their decision to no longer smoke.

We therefore first estimated our baseline models testing H1, H2, and H3 excluding ex-smokers from the estimation sample. The results are presented in Table 7.7 in Panels A, B, and C respectively. The results are largely consistent with our baseline estimates across all three models, except the estimated treatment effect of the ban for continuing smokers is not quite statistically significant, although the point-estimate remains almost identical in magnitude. This is likely due to larger standard errors being driven by the reduced sample size when excluding ex-smokers from the model.

Subsequently, we differentiated between 'Never Smokers', 'Ex-Smokers', and 'Current Smokers' and re-estimated the models replacing the binary smoking status variable with this categorical variable. This was only possible for the models testing H1 and H3 as our quitting variable was colinear with the ex-smoking category. The results are presented in Panels A and B of Table 7.8 respectively. In Panel A, we continue to find that current smokers did not exhibit significantly higher frequencies of depressive feelings during the ban. However, we interestingly find that the treatment effect of the ban on ex-smokers was negative and statistically significant, suggesting that ex-smokers exhibited better mental health whilst the ban was in place relative to never smokers. This may indicate that ex-smokers felt the ban reinforced their commitment to not smoking. Our results from testing H3 continue to indicate that female smokers exhibited significantly elevated frequencies of depressive feelings during the ban, but not male smokers. As in Panel A, we also find that ex-smokers exhibited significantly less frequencies of depressive feelings during the ban relative to never smokers, however this did not vary significantly by gender.

8. Conclusion

8.1 Summary of Findings

On 25 March 2020, the South African government announced a ban on the sale of production of tobacco products was to be implemented from 27 March in response to the COVID-19 pandemic. The ban was finally lifted on 18 August, nearly five months after its inception. The ban provided a quasi-natural experimental setting; whilst all other COVID-19 restrictions in place were common to both smokers and non-smokers, the ban was essentially only relevant to smokers. This enabled a treatment group of smokers and a control group of non-smokers to be defined to estimate the impact the ban had on smokers' mental health.

Using individual-level panel data consisting of five pre-ban waves (2008 to 2017), one during ban wave (June to August 2020), and two post-ban waves (November 2020 to May 2021), we estimated the effect of the ban on smokers' frequencies of depressive feelings using difference-in-difference estimation techniques. Our models controlled for individual-level, time, and provincial fixed effects, and we adjusted the first and second moments of non-smokers' observed characteristics to exactly match those of smokers using entropy balancing to enhance causal inference.

We firstly found a positive but not statistically significant estimate for the effect of the ban on the frequency of depressive feelings for individuals who confirmed they smoked in the week before the ban was implemented. Next, we differentiated between pre-ban smokers who indicated they did and did not continue smoking during the ban. We found that the ban had a weakly statistically significant positive effect on the frequency of depressive feelings exhibited by continuing smokers during the ban, but no effect on those who quit. The size of this effect on continuing smokers was equivalent to 1.39 times increase in the pre-ban sample mean. Finally, we differentiated between female and male pre-ban smokers, finding the ban was associated with a large increase in frequency of depressive feelings for female smokers only. This effect for female smokers was equivalent to a 1.62 times increase in the pre-ban sample mean, and was strongly statistically significant.

8.2 Strengths and Limitations

This study has numerous strengths. Firstly, the quasi-natural experimental setting combined with longitudinal panel data enabled us to employ a robust estimation strategy to estimate the 'treatment' effect of the tobacco sales ban on smokers. We further enhanced this design by deploying entropy balancing techniques to weight our sample of smokers and non-smokers to have near-exactly equivalent covariate distributions, thereby approximating a randomised control trial (Neuenkirch and Neumeier, 2016). This significantly improved on the only known previous study containing information on the impact of the tobacco sales ban on smokers' mental health,

which obtained qualitative findings from a single survey near the start of the ban in which smokers expressed it had caused them feelings of anger, depression, and anxiety (van Walbeek *et al.*, 2020). Our findings suggest that towards the end of the ban, these feelings may have subsided if we treat smokers as a single collective. However, we provided novel evidence that even several months into the ban, individuals who continued smoking as opposed to quit, and female smokers compared to male smokers, were still exhibiting significantly elevated frequencies of depressive feelings.

However, this study is not without limitations. Firstly, depression data was not available in wave 1 of the NIDS-CRAM during the early weeks of the ban, only being collected in the NIDS-CRAM second wave which began approximately three months after the ban had been in place. This precluded the possibility of exploring if the mental health effects of the ban on smokers evolved over time. Second, we relied on self-reported data from smokers' regarding their smoking behaviour during the ban. This was collected in a single wave of the NIDS after the ban had ended, and therefore we relied of retrospective recall of the individuals' consumption of cigarettes before and during the ban. It is further plausible that some individuals stated they had refrained from smoking during the ban in fear of being negatively perceived by the NIDS-CRAM interviewers. Third, due to the NIDS and NIDS-CRAM administering different depression measures, it was only possible to use a single comparable question regarding frequency of depressive feelings and not a full index. As such, the results cannot be interpreted as indication of clinical depression, but rather a reflection of how often the respondent reported recently having feelings of depression. Fourth, there were relatively high rates of attrition between some waves of the NIDS, meaning the final sample may not be fully nationally representative. Fourth, although entropy balancing significantly improves our estimation strategy, it can only equivalise the sample moments of observed characteristics between smokers and non-smokers. That said, the use of individual-level fixed effects allowed us to control for time-invariant unobserved heterogeneity, reducing the likelihood of our results being driven by unobserved individual differences between smokers and non-smokers.

A further limitation is that our DD identification strategy relied on the assumption that only smokers would be affected by the implementation of the tobacco sales ban. We argued that since all other restrictions would be common to both smokers and non-smokers, both in terms on the ban of the sale of other non-essential items and lockdown conditions, this would be sufficient for us to isolate the effect of the ban on smokers' mental health. However, there are some potential challenges to this identification strategy which should be acknowledged. Firstly, Yang and Zucchelli (2018) found some evidence than the implementation of a less stringent ban on smoking

in public places in the UK in 2007 may have had positive externalities on the wellbeing of non-smokers in couples (both with and without a potential smoker spouse). In our study, it is plausible that non-smokers who live with smokers could benefit from the ban should their partner or other smoking household member quit smoking. If this was the case, then this may mean our estimated treatment effect of the ban on smokers is understated, since the frequency of depressive feelings of their comparator (non-smokers) declined during the ban. On the other hand, non-smokers within a household may suffer if smokers within the household chose to smoke more inside their residence to conceal their cigarette consumption. If this was true, then our estimated treatment effect would be overstated since non-smokers also exhibited increased frequencies of depressive feelings as a result of the ban. Further analysis could be conducted to identify whether such spillover effects occurred, which would indicate whether this possibility would indeed be a challenge to our identification strategy. Second, it is plausible that smokers and non-smokers exhibit different propensities to consume other types of non-essential items which were restricted from production and sale. For example, in the first weeks of the ban alcohol sales were prohibited and gambling venues were closed, and it is possible that smokers may be more likely to be consumers of these goods given their apparent preference for risky behaviours. As such, our estimated treatment effect may be overstated if smokers' inability to access other non-essential items also negatively influenced their mental health. However, it should be noted that at the time of interview in our sample during the tobacco sales ban, both activities had been made permissible.

Finally, we conducted complete case analysis whereby individuals with missing data on one or more variables included in our regression models were omitted. However, we provided some evidence that suggests this missingness was likely to be MAR, i.e., related to observable characteristics of our sample (Table G1 in Appendix 2G). As such, our estimates may be biased in the complete case analysis. An extension of this work would be to conduct multiple imputation to address this, which if the data are MAR as suspected, would lead to unbiased estimates (Graham, 2009). This would likely be particularly beneficial given the relatively high rate of missing data in the NIDS and NIDS-CRAM.

8.3 Policy Implications and Future Research

Given this analysis was conducted after the ban was lifted in South Africa, there are limited direct policy implications. Though, there is clear alignment with the findings of existing studies in stating the ban should not have been put in place (van Walbeek *et al.*, 2020; van Walbeek *et al.*, 2021; van der Zee *et al.*, 2023; van Walbeek *et al.*, 2023).

The findings of this study are however relevant in guiding future smoking policy. Indeed, reducing smoking rates within populations is one of the key public health aims of many countries. The present findings suggest that an outright ban on the production and sale of tobacco is not the correct policy to pursue. Alongside the economic impacts found by other papers, such as a loss of tax revenue and entrenching of the illicit market, such a ban may cause significant psychological and emotional distress to smokers.

The finding that the mental health of those who continued to smoke was still being negatively impacted several months into the ban, whilst those who had quit smoking were no longer affected, further highlights the importance of providing adequate cessation support to smokers. Indeed, previous findings suggested that whilst almost half of smokers attempted to quit at the beginning of the ban, as little as 7% were successful towards the end of the ban (van Walbeek *et al.*, 2023). These failed cessation attempts for those who relapsed may have been the significant contributing factor to the negative mental health effects of the ban. The results further suggest that female smokers particularly need to be provided with appropriate support with cessation attempts, as they may be both more likely to relapse and be more susceptible to negative mental health effects from relapsing.

Taken together, the results from this study and previous studies exploring the market and behavioural impact of the ban (van Walbeek *et al.*, 2020; van Walbeek *et al.*, 2021; van der Zee *et al.*, 2023; van Walbeek *et al.*, 2023) indicate that policymakers should pursue market-based policies to reduce smoking rates, as well as focussing on providing accessible and affordable tools for smoking cessation and provide mental health support for those who are trying to stop smoking. Such support was denied to smokers during the ban. Future research should continue to explore the efficacy of such policies. A recent policy development of interest is the decision of the New Zealand government to gradually make the purchase of tobacco illegal by birth year, such that individuals born on or after 1 January 2009 will never be legally allowed to purchase tobacco products (New Zealand. Ministry of Health, 2022). Future research should explore the effects of this closely.

Chapter Three: Tables and Figures

Table 5.1. Description of Variables

Variable	Description	Notes	Type	Waves	Expected Association
Dependent Variable					
Frequency of Depressive Feelings	Ordinal variable for frequency of individual's depressive feelings: = 0 if individual reports depressive feelings 'rarely' or 'not at all', = 1 if individual reports depressive feelings 'some of the time' or 'several days', = 2 if individual reports depressive feelings 'a moderate amount of the time' or 'more than half the days', = 3 if individual reports depressive feelings 'all of the time' or 'nearly every day'.	For the NIDS, derived from CESD-10. Specifically, individuals are asked to state how often they felt 'depressed' n the past week. The four possible responses are: = 0 if 'rarely or none of the time (less than 1 day)', = 1 if 'some or little of the time (1-2 days)', = 2 if 'occasionally or a moderate amount of the time (3-4 days)', or = 3 if 'all of the time (5-7 days)'. For the NIDS-CRAM, derived from the PHQ-2 question: 'Over the past 2 weeks, have you been feeling down, depressed, or hopeless?'. The four responses are: = 0 if 'not at all', = 1 if 'several days', = 2 if 'more than half the days', = 3 if 'nearly every day'. Responses from the NIDS and NIDS-CRAM are combined into a variable reflecting frequency of depressive feelings. Treated as continuous in the baseline analysis. Treated as count in a robustness check.	Ordinal Continuous Count	1-5 (NIDS), 7,8, and 10 (NIDS-CRAM)	N/A
Moderate-to-High Frequency of Depressive Feelings	Dummy variable = 1 if individual reports 2 or more on the scale of frequency of depressive feelings, 0 otherwise.	Utilised in a robustness check using linear probability model.	Binary	1-5 (NIDS), 7,8, and 10 (NIDS-CRAM)	N/A
Key Variables of Interest					
Smoker	Dummy variable = 1 if individual is a smoker, = 0 otherwise	For the NIDS, derived from the question 'do you smoke cigarettes regularly?' = 1 if 'yes', = 0 otherwise	Binary	1-5 (NIDS), 6-10 (NIDS-CRAM)	Positive

Variable	Description	Notes	Type	Waves	Expected Association
		For the NIDS-CRAM, derived from the question 'did you smoke cigarettes in the week before lockdown (before 27th of March 2020)? = 1 if 'yes', = 0 otherwise. Note this was only asked in wave 8 (NIDS-CRAM wave 3), however as the question refers to a time-period before the collection of all NIDS-CRAM data the answer is imputed to the other waves. For subsequent NIDS waves this captures individuals who stated they smoked a positive number of cigarettes in the past week (after the lifting of the ban)			
Continuer	Binary variable = 1 if individual is continued smoking during the ban, = 0 otherwise	In the NIDS-CRAM (waves 6-10), individuals who were pre-ban smokers were asked how many cigarettes they typically smoked per day during the lockdown (*i.e.*, tobacco sales ban) with those who provided a non-negative number coded as continuing smokers during the ban. Only used for testing *H2*.	Binary	1-5 (NIDS), 6-10 (NIDS-CRAM)	Positive
Female	Dummy variable = 1 if individual is male, = 0 otherwise	Not included in linear fixed effects regression unless interacted with smoking status and the tobacco sales ban as time-invariant.	Binary	1-5 (NIDS), 6-10 (NIDS-CRAM)	Negative
Ban	Dummy variable = 1 if individual was interviewed during the tobacco sales ban (27/03/20 to 17/08/20), = 0 otherwise	Equivalent to a binary variable for being interviewed in wave 7 as the interview period begins during the ban and finishes whilst the ban is still in place.	Binary	1-5 (NIDS), 6-10 (NIDS-CRAM)	None
Individual- and Household-Level Control Variables					
Race: Black African	Dummy variable = 1 if individual is Black African, = 0 otherwise	Omitted as reference category in analysis Not included in linear fixed effects regression as time invariant	Binary	1-5 (NIDS), 6-10 (NIDS-CRAM)	N/A
Race: Coloured	Dummy variable = 1 individual is Coloured, = 0 otherwise	Not included in linear fixed effects regression as time invariant	Binary	1-5 (NIDS), 6-10 (NIDS-CRAM)	Negative

Variable	Description	Notes	Type	Waves	Expected Association
Race: Asian/Indian	Dummy variable = 1 if individual is Asian/Indian, = 0 otherwise	Not included in linear fixed effects regression as time invariant	Binary	1-5 (NIDS), 6-10 (NIDS-CRAM)	Negative
Race: White	Dummy variable = 1 if individual is White, = 0 otherwise	Not included in linear fixed effects regression as time invariant	Binary	1-5 (NIDS), 6-10 (NIDS-CRAM)	Negative
Age	Individual's age in years	Sample is restricted to those aged 18 and over as this is the legal age to purchase cigarettes	Continuous	1-5 (NIDS), 6-10 (NIDS-CRAM)	Positive
Age Squared	Individual's age squared	None	Continuous	1-5 (NIDS), 6-10 (NIDS-CRAM)	Negative
Employment Status: Not Economically Active	Dummy variable = 1 if individual is not economically active, = 0 otherwise	Omitted as reference category	Binary	1-5 (NIDS), 6-10 (NIDS-CRAM)	N/A
Employment Status: Unemployed	Dummy variable = 1 if individual is unemployed, = 0 otherwise	Combines the 'strict' and 'discouraged' definitions of unemployment	Binary	1-5 (NIDS), 6-10 (NIDS-CRAM)	Positive
Employment Status: Employed	Dummy variable = 1 if individual is employed, = 0 otherwise	None	Binary	1-5 (NIDS), 6-10 (NIDS-CRAM)	Negative
Highest Education: No Schooling	Dummy variable = 1 if individual has no schooling, = 0 otherwise	Omitted as reference category	Binary	1-5 (NIDS), 6-10 (NIDS-CRAM)	N/A
Highest Education: Primary	Dummy variable = 1 if individual's highest education is junior primary (Grades 0-7 and	Includes school grades 0 to 7, and Adult Basic Education and Training (ABET) levels 1-3.	Binary	1-5 (NIDS), 6-10 (NIDS-CRAM)	Negative

Variable	Description	Notes	Type	Waves	Expected Association
	ABET Levels 1-3), = 0 otherwise				
Highest Education: Grades 8-9 (or equivalent)	Dummy variable = 1 if individual's highest education is Grades 8 to 9 (last two years of compulsory education) or ABET level 4, = 0 otherwise	Includes school grades 8 and 9 (the final two years of compulsory education), Adult Education and Training (ABET) level 4, and National Certificate: Vocational (NCV) level 1. Note Grade 9, ABET level 4, and NCV level 1 are equivalent to National Qualification Framework (NQF) level 1.	Binary	1-5 (NIDS), 6-10 (NIDS-CRAM)	Negative
Highest Education: NQF 2-4	Dummy variable = 1 if individual's highest education is equivalent to NQF 2-4 (Grades 10-12, NTC 1-3, NCV 2-4), = 0 otherwise	Includes school grades 10 to 12, National Technical Certificate (NTC) levels 1 to 3, and National Certificate: Vocational (NCV) levels 2 to 4. Note Grade 10, NTC 1, and NCV 2 are equivalent to NQF level 2, Grade 11, NTC 2, and NCV 3 are equivalent to NQF level 3, and Grade 12, NTC 3, and NCV 4 are equivalent to NQF level 4.	Binary	1-5 (NIDS), 6-10 (NIDS-CRAM)	Negative
Highest Education: Tertiary	Dummy variable if individual's highest education level if tertiary education, = 0 otherwise	Includes all levels of tertiary education such as higher certificates, diplomas, bachelor's degrees, honour's degrees, master's degrees, and doctorates.	Binary	1-5 (NIDS), 6-10 (NIDS-CRAM)	Negative
Marital Status: Married or Living with Partner	Dummy variable = 1 if individual is married or living with a partner, = 0 otherwise	None	Binary	1-5 (NIDS), 6-10 (NIDS-CRAM)	Negative
Real Total Monthly Household Income Per Capita	Real total household income per capita (household member) in Rand	Total household monthly income, divided by household size and deflated to May 2021 prices (source: http://www.statssa.gov.za/publications/P0141/CPIHistory.pdf?) Household monthly income was not elicited in wave 8 (NIDS-CRAM wave 3). In ordered to retain observations, the mean value of real total monthly household income per capita from wave 7 and 9 was imputed to wave 8.	Continuous	1-5 (NIDS), 6-10 (NIDS-CRAM)	N/A

Variable	Description	Notes	Type	Waves	Expected Association
		To remove outliers, the 1% tails of the distribution were set to missing. Not included in model.			
Log of Real Total Monthly Household Income Per Capita	Natural logarithm of real total household income per capita in Rand	Natural logarithm of real total monthly household income per capita (household member). Included in model.	Continuous	1-5 (NIDS), 6-10 (NIDS-CRAM)	Negative
Household Receipt of Government Grant	Dummy variable = 1 if an individual in the household received any form of government grant in the previous month, = 0 otherwise	Derived in NIDS for household-level response to receipt of any of the following in the past month: state old age grant, disability grant, child support grant, foster care grant, care dependency grant, or war veterans' pension. Derived in NIDS-CRAM from individual-level response to receipt of any of the following in the past month: state old age grant, disability grant, child support grant, foster care grant, care dependency grant, or war veterans' pension. This was then utilised to create a household-level variable reflecting if any member of the household stated they received any of these grants.	Binary	1-5 (NIDS), 6-10 (NIDS-CRAM)	Negative
Geo-type: Traditional	Dummy variable =1 if individual lives in a 'Traditional' geographical area (2011 census definition), = 0 otherwise	'Traditional' is defined as 'Communally-owned land under the jurisdiction of traditional leaders. Settlements within these areas are villages' (source: http://www.nids.uct.ac.za/images/documents/20180831-NIDS-W5PanelUserManual-V1.0.pdf) Omitted as reference category.	Binary	1-5 (NIDS), 6-10 (NIDS-CRAM)	N/A
Geo-type: Urban	Dummy variable =1 if individual lives in an 'Urban' geographical area (2011 census definition), = 0 otherwise	'Urban' is defined as 'A continuously built-up area that is established through township establishments such as cities, towns, 'townships', small towns, and hamlets' (source: http://www.nids.uct.ac.za/images/documents/20180831-NIDS-W5PanelUserManual-V1.0.pdf)	Binary	1-5 (NIDS), 6-10 (NIDS-CRAM)	Positive

Variable	Description	Notes	Type	Waves	Expected Association
Geo-type: Farms	Dummy variable =1 if individual lives in a 'Farms' geographical area (2011 census definition), = 0 otherwise	'Farms' is defined as 'land allocated for and used for commercial farming including the structures and infrastructure on it' (source: http://www.nids.uct.ac.za/images/documents/20180831-NIDS-W5PanelUserManual-V1.0.pdf)	Binary	1-5 (NIDS), 6-10 (NIDS-CRAM)	Positive
Household Size	Number of household members	None	Continuous	1-5 (NIDS), 6-10 (NIDS-CRAM)	Negative
Notes: Expected association of independent variables with frequency of depressive feelings are based on findings from the literature on socioeconomic determinants of depression (refs) and studies utilising NIDS and NIDS-CRAM data to conduct depression outcome regressions (refs). Expected association is based on point estimates from studies rather than statistical significance of estimate coefficients. Race and Gender indicators are omitted in linear fixed effects models but are still utilised in the analysis for entropy balancing and/or for interacting with smoking status and the tobacco ban indicator.					

Table 5.2. Descriptive Statistics for Baseline Sample

Variable	Mean	S.D.	Minimum	Maximum
Dependent Variable				
Frequency of Depressive Feelings	0.627	0.833	0	3
Frequency of Depressive Feelings = 0	0.562	0.496	0	1
Frequency of Depressive Feelings = 1	0.289	0.453	0	1
Frequency of Depressive Feelings = 2	0.108	0.311	0	1
Frequency of Depressive Feelings = 3	0.041	0.197	0	1
Moderate-to-High Frequency of Depressive Feelings	0.149	0.356	0	1
Independent Variables				
Smoker	0.184	0.398	0	1
Continuer	0.005	0.069	0	1
Tobacco Sales Ban	0.045	0.208	0	1
Female	0.612	0.487	0	1
Race: Black African	0.828	0.377	0	1
Race: Coloured	0.132	0.338	0	1
Race: Asian/Indian	0.010	0.101	0	1
Race: White	0.030	0.170	0	1
Age	40.430	16.729	18	110
Employment Status: Not Economically Active	0.409	0.492	0	1
Employment Status: Unemployed	0.187	0.390	0	1
Employment Status: Employed	0.405	0.491	0	1
Highest Education: No Schooling	0.102	0.303	0	1
Highest Education: Primary	0.200	0.400	0	1
Highest Education: Grades 8-9	0.141	0.348	0	1
Highest Education: NQF 2-4	0.386	0.487	0	1
Highest Education: Tertiary	0.171	0.376	0	1
Marital Status: Married or Living with Partner	0.357	0.479	0	1
Real Total Monthly Household Income Per Capita	R1,268	R1,931	R35	R16,120
Log of Real Total Monthly Household Income Per Capita	R6.473	R1.127	R3.568	R9.688
Household Receipt of Government Grant	0.681	0.466	0	1
Geo-type: Traditional	0.404	0.491	0	1

Geo-type: Urban	0.533	0.499	0	1
Geo-type: Farm	0.064	0.244	0	1
Household Size	5.266	3.387	1	45

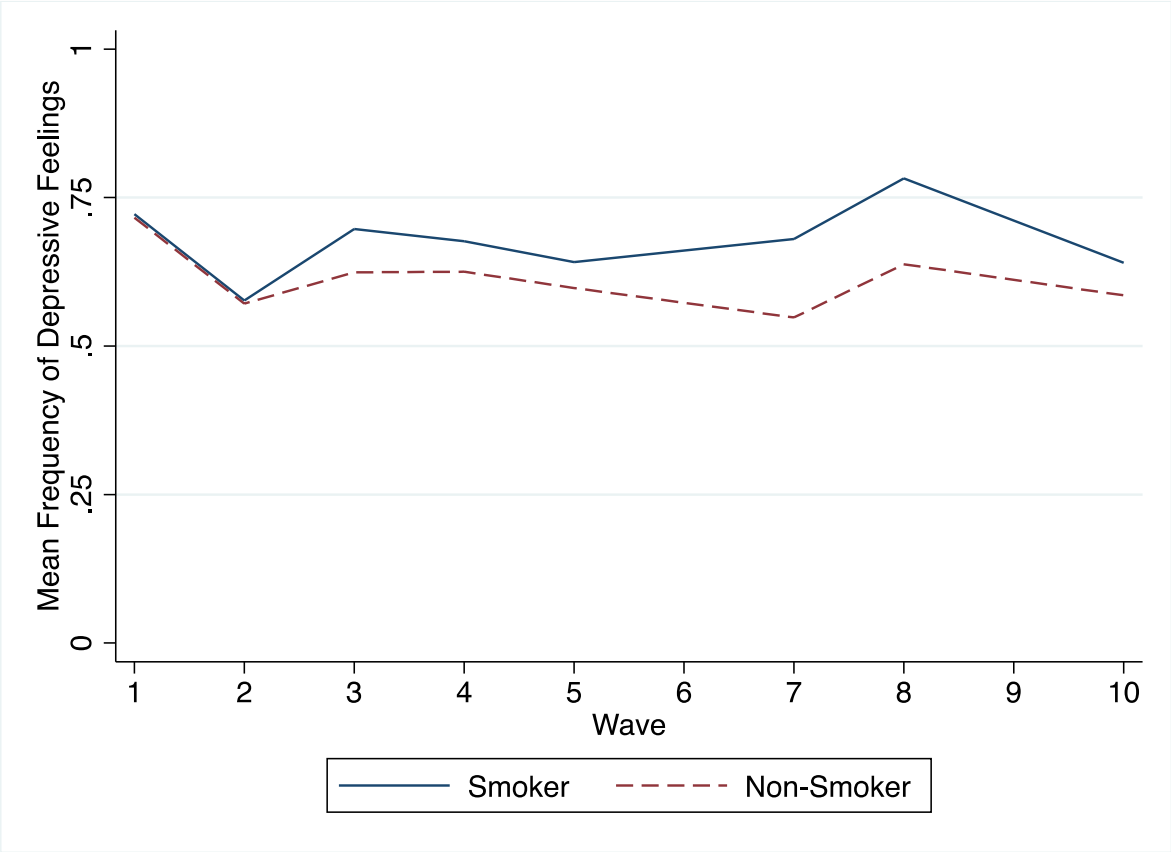
Notes: Statistics reflect the (unweighted) baseline sample (N=85,958) used for testing *H1*, *H2*, and *H3* with linear fixed effects estimation. Figures are correct to three decimal places, except for income which is rounded to the nearest whole number. Statistics for month, wave, and province indicators available in Table B1 in Appendix 2B.

Table 5.3. Frequency of Depressive Feelings by Smoking Status

Variable	Mean Smoker	Mean Non-Smoker	Difference in Mean
Whole Sample (N = 85,958)			
Frequency of Depressive Feelings	0.669	0.618	0.051***
Frequency of Depressive Feelings = 0	0.547	0.566	-0.019***
Frequency of Depressive Feelings = 1	0.286	0.289	-0.003
Frequency of Depressive Feelings = 2	0.118	0.106	0.012***
Frequency of Depressive Feelings = 3	0.048	0.039	0.010***
Pre-Ban (N = 73,617)			
Frequency of Depressive Feelings	0.665	0.622	0.042***
Frequency of Depressive Feelings = 0	0.541	0.550	-0.009*
Frequency of Depressive Feelings = 1	0.295	0.309	-0.014***
Frequency of Depressive Feelings = 2	0.122	0.111	0.011***
Frequency of Depressive Feelings = 3	0.042	0.031	0.011***
During Ban (N = 3,892)			
Frequency of Depressive Feelings	0.680	0.548	0.133***
Frequency of Depressive Feelings = 0	0.631	0.685	-0.054**
Frequency of Depressive Feelings = 1	0.179	0.169	0.010
Frequency of Depressive Feelings = 2	0.068	0.058	0.010
Frequency of Depressive Feelings = 3	0.122	0.088	0.034***
Post-Ban (N = 8,449)			
Frequency of Depressive Feelings	0.721	0.614	0.106***
Frequency of Depressive Feelings = 0	0.585	0.639	-0.053***
Frequency of Depressive Feelings = 1	0.217	0.190	0.028**
Frequency of Depressive Feelings = 2	0.088	0.091	0.002
Frequency of Depressive Feelings = 3	0.109	0.081	0.028***

Notes: Figures correct to three decimal places. Statistical significance is indicated by * at the 10%, ** at the 5%, and *** at the 1% level.

Figure 5. 1 Mean Frequency of Depressive Feelings by Wave and Smoking Status



Note: Mean frequency of depressive feelings not observed in Waves 6 and 9.

Table 7.1. Linear Fixed Effects Regression of Frequency of Depressive Feelings Testing *H1*

Variable	(1) FDF	(2) FDF
	Coefficient (t-statistic)	Coefficient (t-statistic)
Smoker	0.066*** (4.46)	0.065*** (3.79)
Ban	0.094 (1.02)	0.002 (0.01)
Smoker x Ban	0.054 (1.04)	0.058 (0.98)
Age[1]	0.010 (1.21)	0.015 (1.17)
Age Squared[1]	-0.000*** (-9.76)	-0.000*** (-4.76)
Employment Status: Unemployed	-0.022** (-2.13)	-0.012 (-0.72)
Employment Status: Employed	-0.051*** (-4.94)	-0.066*** (-3.89)
Highest Education: Primary	0.042 (1.10)	0.005 (0.08)
Highest Education: Grades 8-9	0.020 (0.45)	0.033 (0.44)
Highest Education: NQF 2-4	0.015 (0.33)	0.064 (0.85)
Highest Education: Tertiary Education	0.019 (0.40)	0.047 (0.62)
Married/Partner Living Together	-0.048*** (-3.63)	-0.049** (-2.40)
Log of Real Household Income Per Capita	-0.028*** (-5.11)	-0.045*** (-5.15)
Receipt of Government Grant	-0.018* (-1.92)	-0.026* (-1.73)
Geo Type: Urban	0.023 (1.26)	0.037 (1.24)
Geo Type: Farm	0.014 (0.49)	0.044 (0.99)
Household Size	-0.003 (-1.50)	-0.009*** (-3.10)
Entropy Balanced	No	Yes
N	85,958	85,958

Notes: All figures correct to 3 decimal places. [1] Precise coefficients on age and its square are 0.0095232 and -0.0003031 in (1) and 0.0148272 and -0.0002691 in (2) respectively. Statistical significance is indicated by * at the 10%, ** at the 5%, and *** at the 1% level. Cluster-robust standard errors are clustered at the individual level. Individual, gender, race, month, wave, and provincial fixed effects absorbed through *reghdfe* command in Stata 17.

Table 7.2. Linear Fixed Effects Regression of Frequency of Depressive Feelings Testing *H2*

Variable	(1) FDF	(2) FDF
	Coefficient (t-statistic)	Coefficient (t-statistic)
Smoker	0.067*** (4.49)	0.065*** (3.81)
Ban	0.094 (1.01)	0.001 (0.01)
Smoker x Ban	-0.152 (-1.13)	-0.154 (-1.10)
Smoker x Ban x Continuer	0.237* (1.66)	0.243* (1.67)
Entropy Balanced	No	Yes
Controls	Yes	Yes
N	85,958	85,958

Notes: All figures correct to 3 decimal places. Statistical significance is indicated by * at the 10%, ** at the 5%, and *** at the 1% level. Models estimated using linear fixed effects regression. Cluster-robust standard errors are clustered at the individual level. Individual, gender, race, month, wave, and provincial fixed effects absorbed through *reghdfe* command in Stata 17. All individual- and household-level controls included but not reported (see Table E1 in Appendix 2E for full results).

Table 7.3. Linear Fixed Effects Regression of Frequency of Depressive Feelings Testing *H3*

Variable	(1) FDF	(2) FDF
	Coefficient (t-statistic)	Coefficient (t-statistic)
Smoker	0.073*** (4.27)	0.074*** (3.82)
Ban	0.138 (1.45)	0.009 (0.06)
Smoker x Ban	-0.060 (-1.00)	-0.024 (-0.35)
Smoker x Female	-0.020 (-0.60)	-0.048 (-1.24)
Ban x Female	-0.068* (-1.94)	-0.041 (-0.80)
Smoker x Ban x Female	0.397*** (3.02)	0.395*** (2.89)
Entropy Balanced	No	Yes
Controls	Yes	Yes
N	85,958	85,958

Notes: All figures correct to 3 decimal places. Statistical significance is indicated by * at the 10%, ** at the 5%, and *** at the 1% level. Models estimated using linear fixed effects regression. Cluster-robust standard errors are clustered at the individual level. Individual, gender, race, month, wave, and provincial fixed effects absorbed through *reghdfe* command in Stata 17. All individual- and household-level controls included but not reported (see Table E2 in Appendix 2E for full results).

Table 7.4. Robustness Check 1: Linear Probability Models for Moderate-to-High Frequency of Depressive Feelings

Panel A: Hypothesis 1		Panel B: Hypothesis 2		Panel C: Hypothesis 3	
Variable	**(1) FDF ≥ 2**	**Variable**	**(2) FDF ≥ 2**	**Variable**	**(3) FDF ≥ 2**
	Coefficient (t-statistic)		**Coefficient (t-statistic)**		**Coefficient (t-statistic)**
Smoker	0.017** (2.39)	Smoker	0.018** (2.41)	Smoker	0.020** (2.38)
Ban	0.041 (0.62)	Ban	0.041 (0.62)	Ban	0.047 (0.70)
Smoker x Ban	0.024 (1.03)	Smoker x Ban	-0.069 (-1.27)	Smoker x Ban	0.002 (0.07)
		Smoker x Ban x Continuer	0.107* (1.87)	Smoker x Female	-0.012 (-0.69)
				Ban x Female	-0.026 (-1.40)
				Smoker x Ban x Female	0.101* (1.83)
Entropy Balanced	Yes	Entropy Balanced	Yes	Entropy Balanced	Yes
Controls	Yes	Controls	Yes	Controls	Yes
N	85,958	N	85,958	N	85,958

Notes: All figures correct to 3 decimal places. Statistical significance is indicated by * at the 10%, ** at the 5%, and *** at the 1% level. Models estimated using linear fixed effects regression. Cluster-robust standard errors are clustered at the individual level. Individual, gender, race, month, wave, and provincial fixed effects absorbed through *reghdfe* command in Stata 17. All individual- and household-level controls included but not reported (see F1 in Appendix 2F for full results)

Table 7.5. Robustness Check 2: Poisson Models for Frequency of Depressive Feelings

Panel A: Hypothesis 1		Panel B: Hypothesis 2		Panel C: Hypothesis 3	
Variable	**(1) FDF**	**Variable**	**(2) FDF**	**Variable**	**(3) FDF**
	IRR (z-statistic)		**IRR (z-statistic)**		**IRR (z-statistic)**
Smoker	1.115*** (4.71)	Smoker	1.115*** (4.72)	Smoker	1.133*** (4.70)
Ban	1.037 (0.18)	Ban	1.037 (0.18)	Ban	1.045 (0.21)
Smoker x Ban	1.097 (1.11)	Smoker x Ban	0.800 (-1.03)	Smoker x Ban	0.956 (-0.42)
		Smoker x Ban x Continuer	1.434* (1.65)	Smoker x Female	0.919* (-1.77)
				Ban x Female	0.932 (-0.86)
				Smoker x Ban x Female	1.685*** (3.42)
Entropy Balanced	Yes	Entropy Balanced	Yes	Entropy Balanced	Yes
Controls	Yes	Controls	Yes	Controls	Yes
N	74,099	N	74,099	N	74,099

Notes: All figures correct to 3 decimal places. Statistical significance is indicated by * at the 10%, ** at the 5%, and *** at the 1% level. Models estimated using Poisson regression with fixed effects. Cluster-robust standard errors are clustered at the individual level. Individual, gender, race, month, wave, and provincial fixed effects absorbed through *ppmlhdfe* command in Stata 17. All individual- and household-level controls included but not reported (see F2 in Appendix 2F for full results). IRR is the incidence-rate ratio, equal to the exponent of the estimated coefficient.

Table 7.6. Robustness Check 3: History of Depression

Panel A: Hypothesis 1			Panel B: Hypothesis 2			Panel C: Hypothesis 3		
Variable	**(1) FDF Exc. Strong History**	**(2) FDF Exc. Recent History**	**Variable**	**(3) FDF Exc. Strong History**	**(4) FDF Exc. Recent History**	**Variable**	**(5) FDF Exc. Strong History**	**(6) FDF Exc. Recent Hisotry**
	Coefficient (z-statistic)	**Coefficient (z-statistic)**		**Coefficient (z-statistic)**	**Coefficient (z-statistic)**		**Coefficient (z-statistic)**	**Coefficient (z-statistic)**
Smoker	0.060*** (3.42)	0.056*** (3.25)	Smoker	0.059*** (3.39)	0.057*** (3.27)	Smoker	0.059*** (3.01)	0.057*** (2.88)
Ban	-0.099 (-0.68)	-0.080 (-0.55)	Ban	-0.100 (-0.68)	-0.080 (-0.55)	Ban	-0.099 (-0.67)	-0.080 (-0.54)
Smoker x Smoke Ban	0.066 (1.12)	0.067 (1.14)	Smoker x Ban	-0.125 (-0.93)	-0.121 (-0.90)	Smoker x Ban	-0.007 (-0.11)	-0.005 (-0.07)
			Smoker x Ban x Continuer	0.220 (1.57)	0.216 (1.54)	Smoker x Female	0.002 (0.06)	0.004 (0.11)
						Ban x Female	-0.015 (-0.28)	-0.013 (-0.25)
						Smoker x Ban x Female	0.363*** (2.67)	0.358*** (2.63)
Entropy Balanced	Yes	Yes	Entropy Balanced	Yes	Yes	Entropy Balanced	Yes	Yes
Controls	Yes	Yes	Controls	Yes	Yes	Controls	Yes	Yes
N	80,139	81,087	N	80,139	81,087	N	80,139	81,087

Notes: All figures correct to 3 decimal places. Statistical significance is indicated by * at the 10%, ** at the 5%, and *** at the 1% level. Models estimated using linear fixed effects regression. Cluster-robust standard errors are clustered at the individual level. Individual, gender, race, month, wave, and provincial fixed effects absorbed through *reghdfe* command in Stata 17. All individual- and household-level controls included but not reported (see Table F4 in Appendix 2F for full results)

Table 7.7 Robustness Check 4a: Removal of Ex-Smokers

Panel A: Hypothesis 1		Panel B: Hypothesis 2		Panel C: Hypothesis 3	
Variable	**(1) FDF**	**Variable**	**(2) FDF**	**Variable**	**(3) FDF**
	Coefficient (t-statistic)		**Coefficient (t-statistic)**		**Coefficient (t-statistic)**
Smoker	0.072*** (3.71)	Smoker	0.073*** (3.72)	Smoker	0.077*** (3.52)
Ban	0.105 (0.67)	Ban	0.104 (0.67)	Ban	0.119 (0.76)
Smoker x Ban	0.017 (0.27)	Smoker x Ban	-0.189 (-1.31)	Smoker x Ban	-0.074 (-0.99)
		Smoker x Ban x Continuer	0.236 (1.59)	Smoker x Female	-0.023 (-0.50)
				Ban x Female	-0.079 (-1.33)
				Smoker x Ban x Female	0.436*** (3.11)
Entropy Balanced	Yes	Entropy Balanced	Yes	Entropy Balanced	Yes
Controls	Yes	Controls	Yes	Controls	Yes
N	79,023	N	79,023	N	79,023

Notes: All figures correct to 3 decimal places. Statistical significance is indicated by * at the 10%, ** at the 5%, and *** at the 1% level. Models estimated using linear fixed effects regression. Cluster-robust standard errors are clustered at the individual level. Individual, gender, race, month, wave, and provincial fixed effects absorbed through *reghdfe* command in Stata 17. All individual- and household-level controls included but not reported (available on request).

Table 7.8 Robustness Check 4b: Differentiation Between Ex- and Current Smokers

Panel A: Hypothesis 1		Panel B: Hypothesis 3	
Variable	**(1) FDF**	**Variable**	**(2) FDF**
	Coefficient (t-statistic)		**Coefficient (t-statistic)**
Smoker	0.070*** (3.65)	Smoker	0.077*** (3.57)
Ex-Smoker	0.026 (0.61)	Ex-Smoker	0.016 (0.34)
Ban	0.052 (0.35)	Ban	0.078 (0.51)
Smoker x Ban	0.003 (0.05)	Smoker x Ban	-0.099 (-1.32)
Ex-Smoker x Ban	-0.271*** (-2.78)	Ex-Smoker x Ban	-0.312*** (-2.74)
		Smoker x Female	-0.034 (-0.76)
		Ex-Smoker x Female	0.052 (0.58)
		Ban x Female	-0.103* (-1.75)
		Smoker x Ban x Female	0.457*** (3.27)
		Ex-Smoker x Ban x Female	0.186 (1.02)
Entropy Balanced	Yes	Entropy Balanced	Yes
Controls	Yes	Controls	Yes
N	85,099	N	85,099

Notes: All figures correct to 3 decimal places. Statistical significance is indicated by * at the 10%, ** at the 5%, and *** at the 1% level. Models estimated using linear fixed effects regression. Cluster-robust standard errors are clustered at the individual level. Individual, gender, race, month, wave, and provincial fixed effects absorbed through *reghdfe* command in Stata 17. All individual- and household-level controls included but not reported (available on request).

Chapter Four: How Did the Big Five Personality Traits Moderate the Effect of Extended Lockdowns on Mental Health in Australia?

1. Introduction

In response to the COVID-19 pandemic, governments worldwide implemented policies aimed at safeguarding public health by reducing community transmission. The most stringent of these measures were 'lockdown' policies which confined citizens to their homes except for essential activities like shopping for necessities or seeking medical care (Woc-Colburn and Godinez, 2022). While effective in curbing COVID-19 cases and fatalities (Woc-Colburn and Godinez, 2022; Herby *et al.*, 2023), concerns arose regarding the unintended impact of such policies on mental health (Bradbury-Jones and Isham, 2020; Santomauro *et al.*, 2021; Woc-Colburn and Godinez, 2022).

A substantial body of empirical research has indicated an association between policy stringency or lockdowns with deteriorating mental health in European and US samples (Garcia-Prado *et al.*, 2022; Adams-Prassl *et al.*, 2022; Toffolutti *et al.*, 2022; Aknin *et al.*, 2022; Brodeur *et al.*, 2021; Arendt *et al.*, 2020; Ramiz *et al.*, 2021; Serrano-Alarcon *et al.*, 2022; Schmidtke *et al.*, 2021). However, many of these studies relied on cross-sectional data across multiple regions or failed to incorporate pre-pandemic data, weakening causal inferences and introducing potential bias by not controlling for pre-pandemic trends (Hale *et al.*, 2023). Studies using pre-pandemic data often employed less robust mental health measures, such as changes in crisis hotline calls or Google search trends for mental wellbeing terms (Arendt *et al.*, 2020; Brodeur *et al.*, 2021). Those utilising more robust mental health measures with individual-level panel surveys faced challenges such as extended gaps between pre-pandemic and pandemic observations, non-representative samples, or weak identification strategies for difference-in-differences (DD) analysis (Ramiz *et al.*, 2021; Schmidtke *et al.*, 2021; Serrano-Alarcon *et al.*, 2022).

Australia offers a unique setting to study the mental health effects of lockdown policies due to its federal governance structure, granting significant policy-making powers to state and territory governments (Australian Government. Department of Foreign Affairs and Trade, 2023). Consequently, significant heterogeneity in COVID-19 policies emerged across states in the latter half of 2020 and throughout 2021 (Edwards *et al.*, 2022). This policy variation presents an ideal quasi-natural experiment to investigate the impact of lockdown on mental health.

While existing research has explored the mental health impact of lockdowns in Australia, most studies focused on disparities between Victorian residents and the rest of the country in 2020 and

were often constrained by cross-sectional data or non-nationally representative samples (Czeisler *et al.*, 2021; Fisher *et al.*, 2021; Leach *et al.*, 2023). Few studies utilised Australian panel data, and only one examined the effects of extended lockdowns on mental health in both 2020 and 2021, which was restricted to state capital cities (Li *et al.*, 2023).

A growing body of literature has sought to identify groups more vulnerable to poor mental health during the pandemic and lockdowns. Two consistent findings are that women and younger adults experienced the most substantial declines in mental health (Ramiz *et al.*, 2021; Adams-Prassl *et al.*, 2022; Garcia-Prado *et al.*, 2022; Hale *et al.*, 2023), potentially due to differences in personality traits (Hale *et al.*, 2023). The association between the 'Big Five' personality traits (extroversion, emotional stability, agreeableness, conscientiousness, and openness to experience) and mental health is well-documented, with all five traits linked to better mental well-being (DeNeve and Cooper, 1998; Malouff *et al.*, 2005; Kotov *et al.*, 2010; McCann, 2010; McCann, 2011; Lamers *et al.*, 2012; Boyce *et al.*, 2015; Hakulinen *et al.*, 2015; Strickhouser *et al.*, 2017; Batty *et al.*, 2018; Lyon *et al.*, 2021). This relationship may be attributed to coping strategies varying with personality traits (Cheng and Furnham, 2001; Mirinics *et al.*, 2013; Panayiotou *et al.*, 2014). Personality traits may also influence mental health through experiences and reactions to negative events, particularly for those with lower emotional stability (Ormel and Wohlfarth, 1991; Ormel *et al.*, 2001; Kendler *et al.*, 2004; Lockenhoff *et al.*, 2009; van der Veen *et al.*, 2017). Hence, personality traits may play an important role in the mental health effects of the COVID-19 pandemic.

Previous empirical work has explored the potential variation in mental health outcomes across individuals with different levels of the Big Five personality traits during the pandemic. However, many studies lacked data to establish causal inferences and merely demonstrated associations (Wei, 2020; Nikcevic *et al.*, 2021; Pauly *et al.*, 2021; Shokkron and Nicoladis, 2021; Zhang *et al.*, 2021a; Zhang *et al.*, 2021b; Margetic *et al.*, 2022; Michinov and Michinov, 2023). Studies employing panel data also had limitations, as they drew data from countries such as Germany and the UK, which enforced uniform national lockdown policies and therefore lacked contemporaneous treatment and control groups (Zacher and Rudolph, 2021; Proto and Zhang, 2021; Staneva *et al.*, 2022).

This chapter contributes to the literature by estimating the impact of extended lockdown policies on mental health in Australia, exploiting the state-level policy heterogeneity. To this end, we employed 17 waves of individual-level panel data from the Household, Income, and Labour Dynamics Australia (HILDA) survey, which spanned from 2005 to 2021. This allowed us to observe individuals under four extended lockdowns (Victoria in 2020 and 2021, and New South Wales and Australian Capital Territory in 2021) and mitigate potential bias using the 'Extended'

Two-Way Fixed Effects (ETWFE) estimator (Wooldridge, 2021). Additionally, we introduced triple difference-in-difference interaction terms to explore the moderating effects of the Big Five personality traits. Our findings revealed that extended lockdowns had a significant adverse impact on the mental health of individuals in affected states, with some variations across cohorts. Extroversion, emotional stability, and openness moderated these effects to varying degrees, indicating that personality traits played a role in how individuals' mental health responded to extended lockdowns.

The subsequent sections of this chapter are structured as follows. Section 2 provides an overview of COVID-19 policies in Australia during 2020 and 2021. Section 3 reviews relevant literature on the mental health impact of COVID-19 policies in Australia and other high-income countries, as well as the association between the Big Five personality traits and mental health. Section 4 outlines the hypotheses tested. Section 5 presents an overview of the HILDA survey and descriptive statistics of the sample. Section 6 details our baseline specification and estimation methods. Section 7 presents our results and robustness tests. Finally, Section 8 concludes by summarising our key findings, discussing strengths and limitations, and suggesting policy implications and avenues for future research.

2. Background

COVID-19, the infectious disease caused by the SARS-CoV-2 virus, was officially declared as a pandemic by the World Health Organisation on 11 March 2020 (World Health Organisation, 2020). In response, the Australian national government implemented a number of policy directives beginning with the closure of all non-essential indoor gatherings of 100 people or more, and of outdoor gatherings of 500 people or more on 18 March 2020. Two days later, Australia closed its international borders to all but Australian Citizens, permanent residents, and their immediate families (The Guardian, 2020). A subsequent national directive dubbed 'National Stage 1 Restrictions' enacted the closure of non-essential businesses from 23 March (Parliament of Australia, 2022). One day later the Australian Prime Minister urged Australians to "stay at home unless it is absolutely necessary you go out" (ABC News, 2020a). State-level governments followed this directive, with individuals across Australia living under 'lockdown' conditions until late April to early May (Butterworth *et al.*, 2022).

Whilst state-level policy responses were relatively homogenous in the initial two-or-so months of the pandemic, significant heterogeneity subsequently arose. States broadly adopted one of two approaches during the second half of 2020 and throughout 2021 (Edwards *et al.*, 2022):

i) Strict border rules and 'snap' lockdowns: generally adopted by states with low COVID-19 exposure, this policy approach implemented hard state borders and short lockdowns, often targeted to localised areas where cases had been detected.

ii) Stringent measures with prolonged lockdowns: generally adopted by states with high COVID-19 exposure, this policy approach implemented prolonged periods of lockdown, which were often state-wide.

During the second half of 2020, Victoria was the only state to implement the prolonged lockdown approach (Butterworth *et al.*, 2022; Li *et al.*, 2023). On 1 July 2020, stay-at-home orders were issued to approximately 311,000 residents living across various Metropolitan postcodes (Australian Government. Department of Health and Aged Care, 2020). These orders were extended to the entire Metropolitan Melbourne and Mitchel Shire area on 9 July 2020 (Blakely *et al.*, 2020). On 2 August 2020, a State of Disaster was declared for Metropolitan Melbourne, bringing with it the imposition of a 20:00 to 05:00 curfew (Victoria State Government. Health and Human Services, 2020a). The rest of Victoria was also placed under stay-at-home orders without the curfew. Despite some slight easing in September 2020 (ABC News, 2020b), stay-at-home orders remained in place until 18 October 2020 for the rest of Victoria, and 27 October 2020 for Greater Melbourne (Victoria State Government. Health and Human Services, 2020b). Thus, some residents of

Melbourne had been under strict lockdown conditions for a total of 111 days (Li *et al.*, 2023). In contrast, Australians residing in all other states had experienced relative freedom from May until the end of 2020 (Butterworth *et al.*, 2022; Li *et al.*, 2023).

In 2021, the governments of New South Wales (NSW) and Australian Capital Territory (ACT) joined Victoria in enacting periods of prolonged lockdowns, whilst the governments of Northern Territory (NT), Queensland, South Australia (SA), Tasmania, and Western Australia (WA) pursued the 'strict borders and snap lockdowns' policy approach (Edwards *et al.*, 2022).

In Victoria, short state-wide lockdowns were implemented on three occasions in February (5 days), May-June (14 days), and July (12 days) (Premier of Victoria, 2021a; Victoria State Government. Health and Human Services, 2021; Premier of Victoria, 2021b). However, on 5 August, the entire state was placed under lockdown restrictions (Australia Bureau of Statistics, 2021). These stay-at-home orders remained in place for the Rest of Victoria until 10 September, whilst Greater Melbourne remained locked down until 22 October 2021 (with some other parts of regional Victoria entering snap lockdowns between these dates) (Australia Bureau of Statistics, 2021). Thus, residents of Greater Melbourne experienced a further 151 days of lockdown in 2021, constituting the world's longest lockdown (Li *et al.*, 2023).

In NSW, some residents of the Northern Beaches area of Sydney had been placed under a snap lockdown in late December 2020 to early January 2021 (The Guardian, 2021). However, the rest of the state avoided such orders until 26 June 2021, when Greater Sydney and the regions of Central Coast, Blue Mountains, Wollongong, and Shellharbour were ordered to stay-at-home for two weeks (Reuters, 2021). This order was extended multiple times, and on 14 August 2021 the Rest of NSW joined these areas in a state-wide lockdown (NSW Government. NSW Health, 2021a). These restrictions were lifted on 11 September 2021 for parts of regional NSW (NSW Government. Small Business Commissioner, 2021), whilst Greater Sydney remained under lockdown until 11 October 2021 (BBC News, 2021). Note that some local government areas (LGAs) in regional NSW were also placed back under lockdown conditions when experiencing high transmission rates up until this date (NSW Government. NSW Health, 2021b).

Finally, residents of ACT had enjoyed approximately 14 months of relative freedom since restrictions were first relaxed in May 2020 (Edwards *et al.*, 2022). However, on 12 August 2021, the state was placed under a 7-day lockdown (Legal Aid ACT, 2021) which was extended multiple times, and ultimately lasted until 14 October 2021 (ACT Government, 2021).

Since Greater Melbourne was lifted from lockdown on 21 October 2021, no further lockdowns have been implemented across Australia, in part thanks to high rates of vaccination (Edwards *et*

al., 2022). The state-level heterogeneity in COVID-19 policies provided an ideal setting to study the impact of extended lockdowns on mental health.

3. Literature Review

This section provides a selective review of the existing literature. It begins with an overview on existing studies on the mental health effects of the pandemic and lockdown policies in Australia. This is subsequently supplemented with evidence from other high-income countries, with a focus on papers which employ estimation methods to enhance causal inference. Next, we present studies which detail the links between the Big Five personality traits and various mental health outcomes, including those which seek to explain potential mechanisms for these links. Subsequently, we review the limited literature on the relationship between the Big Five personality traits and mental health during the pandemic. The section concludes by outlining the contributions this study makes to the literature.

3.1 Mental Health During the COVID-19 Pandemic

3.1.1 The Effect of the COVID-19 Pandemic on Mental Health in Australia

This sub-section provides an overview of existing literature on the mental health impacts of the COVID-19 pandemic in Australia, with a focus on the differential effects among residents in states under lockdown. Most attention was given to Victoria, the only state subjected to extended strict lockdowns in 2020. We first review studies using data collected during the pandemic and then those incorporating pre-pandemic and pandemic data.

Firstly, Czeisler *et al.* (2021) conducted a study on the prevalence and risk factors of adverse mental health outcomes and behaviours in two cross-sectional samples of residents of Victoria. The first sample included 334 Victorian residents surveyed in April 2020, with a follow-up survey in September 2020 involving 92 participants from the initial group and an additional 1,249 Victorian residents. The study primarily calculated prevalence rates of various mental health and wellbeing measures across these two survey samples and examined statistical differences between them. The results indicated that high prevalence rates of adverse mental health outcomes, including symptoms of depression and anxiety (33%) and burnout (26%), were present in the September 2020 sample. However, these rates were not statistically different from those in the April 2020 sample, suggesting that adverse mental health rates persisted but did not worsen in Victoria despite prolonged lockdown measures. Nevertheless, the cross-sectional nature of the data limited the ability of the study to establish causation or make comparisons with other Australian regions.

Improving on this, Fisher *et al.* (2021) investigated the mental health impact of the extended lockdown in Victoria in 2020 using a national-level sample of 23,749 observations obtained from two cross-sectional surveys. The first survey was conducted in April 2020, while the second took place in July/August 2020 shortly after the imposition of lockdown in Victoria. The authors

employed a difference-in-differences (DD) analysis to estimate the treatment effect of lockdown restrictions on various mental health outcome measures, including clinically significant symptoms of depression, anxiety, thoughts of suicide or self-harm, irritability, and optimism about the future. The results revealed that individuals residing in Victoria during the state lockdown had higher odds of depression and anxiety and lower odds of optimism about the future compared to the rest of Australia. This indicated that severe lockdown restrictions had a significant negative impact on mental health. However, although the study does employ a DD design, this was limited by the cross-sectional nature of the data meaning repeated observations on the same individuals were not available. Furthermore, the samples were obtained from online survey, raising concerns about the generalisability of the results.

Subsequent studies have employed more robust empirical designs by utilising both pre- and during-pandemic data. Firstly, Leach *et al.* (2023) explored the psychological health of 1,266 employed Australian parents during the COVID-19 pandemic, comparing data from August 2020 with information collected in August 2016. The study used random and fixed-effects models of psychological distress, with the key variable of interest being an indicator for the August 2020 wave. The study firstly found an increase in psychological distress during the pandemic compared to pre-pandemic levels. This increase was more pronounced for parents residing in Victoria. Despite improving on preceding studies by including pre- and during-pandemic data, the study was still limited in its generalisability as the sample consisted only of working parents. Furthermore, the four-year gap between interviews meant that the results may have been biased by unaccounted trends in mental health.

Butterworth *et al.* (2022) improved further on the preceding studies by 151,583 observations on individuals from ten waves of the nationally representative Household, Income, and Labour Dynamics in Australia (HILDA) survey. This comprised annual pre-COVID-19 data from 2011 to 2019 and a single wave of during COVID-19 data for 2020. Employing a quasi-natural experimental design, residents of Victoria were treated as the treatment group for in a DD regression analysis, with the Mental Health Inventory 5 (MHI-5) score serving as the primary mental health outcome measure. The results indicated that lockdown measures in Victoria significantly reduced mental health, equivalent to a 1.4-point reduction in MHI-5 scores. Sub-group analyses revealed that females, particularly those in couples with young children or living in certain types of housing, were most negatively affected by lockdown. The causal inferences of the study were strengthened by the quasi-natural experimental design. However, only one during-COVID-19 data point was available, meaning the duration and persistence of the estimated mental health effects could not be explored.

Addressing this, Li *et al.* (2023) examined the impact of green and blue spaces on mental health during extended lockdowns in 2020 and 2021 using data from ten waves of the HILDA survey spanning 2012 to 2021. By incorporating data from wave 21 of the HILDA survey, the authors were able to analyse not only the 2020 Victorian lockdown but also the extended lockdowns in Victoria, NSW, and ACT in 2021. Their analysis focused on Greater Capital Cities to enable causal inference to be based on regions more comparable in green and blue space. Mental health was measured using the MHI-5. Data on green and blue spaces was obtained from the ABS 2016 census. Green space was categorised into five groups ranging from 0 to 5% to 30% or more coverage, while inland blue space was indicated by a binary variable for any coverage, and coastal blue space was defined by proximity to the coastline. The authors estimated MHI-5 as a function of the green and blue space variables, lockdown indicators, and their interaction terms, while socioeconomic and demographic factors, and time and state fixed effects. The models were estimated using the extended two-way fixed effects (ETWFE) with staggered interventions (Wooldridge, 2021).

The results indicated that exposure to extended lockdowns in 2020 and 2021 were respectively associated with a 2.66- and 2.65-point decline in mental health scores compared to pre-COVID-19 levels. Additionally, higher percentages of green and blue space coverage were associated with reduced mental health effects during the extended lockdowns in both years. The study's strength lay in its use of longitudinal data, including pre-pandemic observations and data from both 2020 and 2021. This, combined with the quasi-natural experimental setting arising from varying state-level COVID-19 policies, strengthened causal inferences, and allowed for the assessment of differential effects of extended lockdowns in 2020 and 2021 on mental health. However, the analysis focused solely on the Greater Capital Cities, and therefore did not consider the rest of state regions of Victoria and NSW which also experienced extended lockdowns during this period. Furthermore, the study did not consider heterogeneity in cohort effects between Greater Melbourne, who were exposed to their second (post-national) extended lockdown in 2021, and Greater Sydney and ACT who were exposed to their first in 2021.

Finally, Hale *et al.* (2023) conducted a study investigating disparities in distress levels across age groups before and during the COVID-19 pandemic. The study first analysed trends in household panel data from Australia, the UK, and the US, revealing that distress had been rising among younger and middle-aged groups before the pandemic, while it had remained relatively stable among older age groups. Notably, the rate of distress increase was highest among the youngest age group compared to the middle age group. The authors emphasised that disregarding these pre-pandemic distress trends would exaggerate the pandemic's impact. Next, they explored the extent

to which distress during the first year of the pandemic could be attributed to lockdowns and whether age-related distinctions in distress changed during this period. Trend analysis indicated that lockdowns contributed to heightened distress in the US, UK, and Australia. In the UK, lockdowns affected individuals across age groups, but the magnitude of distress fluctuations during lockdown implementation and lifting was most significant among younger adults and least pronounced among older adults. While these observations suggested that social deprivation might have been a primary contributor to pandemic-related distress, it was acknowledged that the coincidence of lockdowns with elevated COVID-19 infection rates made definitive conclusions challenging without controlling for these factors.

Subsequently, the authors theorised that the observed individual and age-based variations in trends in psychological distress both pre- and during the pandemic could be attributed to personality traits. Specifically, they proposed that emotional stability, which tends to increase with age, could moderate the relationship between stressors and psychological distress. This hypothesis aligned with observed distress patterns across age groups, both before and during the pandemic. Additionally, the authors speculated that this might explain why women appeared to experience greater distress during the pandemic in the UK and Australia, given that women generally exhibit lower emotional stability compared to men. The study suggested that other age-varying traits, like conscientiousness, might also contribute to these observed trends. However, they did not empirically test for the possible moderating role of personality traits. Consequently, they recommended further empirical investigation into the role of personality traits in shaping individuals' susceptibility to stressors and their effects on psychological distress.

3.1.2 The Effect of Lockdowns and Policy Stringency on Mental Health in Other High-Income Countries

This sub-section reviews studies which have estimated the effect of lockdown policies or COVID-19 policy stringency on mental health in other high-income countries, focussing on those which employed more robust methodologies for causal inference.

Firstly, Garcia-Prado *et al.* (2022) conducted a cross-sectional DD analysis on the impact of lockdowns on the mental health of individuals aged 50 years and over from 16 European countries and Israel. A total of 40,501 observations from the Survey of Health Ageing and Retirement (SHARE) survey collected between June and August 2020 were utilised in conjunction with policy stringency data from the from the Oxford COVID-19 Government Response Tracker (OxCGRT). The authors also utilised data from the 2015-16 SHARE to estimate the probability of an individual having a high frequency of face-to-face interactions pre-pandemic. Such

individuals were defined as the treatment group for the analysis, which was then exploited alongside country-level heterogeneity in the policy stringency to obtain causal estimates for the impact of lockdown strictness on mental health. The study found that strict lockdown policies were associated with a significant worsening of anxiety, depression, and insomnia by 7.2, 5.1, and 5.0 percentage points, respectively. These effects were particularly pronounced in younger adults aged 50 to 65 and women. While the study benefitted from a substantial sample size and the use of DD estimation for causal inference, the generalisability of the findings is limited to older age groups.

Adams-Prassl *et al.* (2022) instead exploited heterogeneity in state-wide lockdown policies on the mental health of 12,010 economically active individuals in the United States. The study utilised three waves of data from March, April, and May 2020, during which time states with lockdowns increased from 13 to 40 between March and April, before falling to 24 by the end of May. This variation was utilised to estimate the effect of lockdowns on mental health scores, with the study firstly finding that mental health scores were 0.083 standard deviations lower in states with lockdown orders compared to those without. Additional analysis then pooled the three survey waves to exploit changes in lockdown status over time, which similarly revealed on negative impact of lockdown on the mental health. Finally, the study estimated a significant gender gap in these effects, with the observed reductions in mental health found to be solely driven by women under lockdown. Potential mechanisms for explaining this gender difference, such as financial worries, caring responsibilities, and the number of Covid-19 cases or deaths per capita, were ruled out through further analysis.

The preceding two studies exploited cross-country or cross-state differences in policies using data collected relatively early into the pandemic. Toffolutti *et al.* (2022) instead utilised three waves of data from the Eurofound 'Living, Working, and Covid-19' survey which covered covering a longer from April 2020 to March 2021. The authors examined the associations between the implementation and lifting of 13 different non-pharmaceutical policy interventions (NPIs) aimed at controlling the Covid-19 pandemic and mental wellbeing (MWB) in 28 European countries. The 13 NPIs, which included restrictions such as workplace closures and stay-at-home orders, were derived from the Oxford COVID-19 Government Response Tracker (OxCGRT). A sample of 15,147 observations was utilised to estimate regression models for each NPI, with MWB estimated as a function of an indicator for the given NPI being in place, socioeconomic and demographics characteristics, and daily information on country-level COVID-19 cases and deaths. The study revealed that restrictions on international travel, private gatherings, and contact tracing were negatively associated with MWB, while workplace closures exhibited a positive association.

Heterogeneity analysis indicated that women fared worse than men under various NPIs including stay-at-home requirements and school-closures, which the authors noted may reflect an increased burden of childcare on women. The strengths of the study include its use of longitudinal data covering three differing periods of the pandemic across 28 countries and its detailed analysis of multiple NPIs. However, it was limited by a lack of pre-pandemic data and by only estimating associations rather than identifying causal effects.

Aknin *et al.* (2022) utilised fortnightly cross-sectional data on 432,000 individuals covering the period of April 2020 to June 2021 to explore the impact of policy stringency on mental health in 15 high-income countries, including Australia. The data were drawn from the Imperial College London YouGov COVID-19 Behaviour Tracker Global Survey, with mental health measured using the PHQ-4 for psychological distress and the Cantril Ladder for life evaluation. Policy stringency data for each country was obtained from the OxCGRT. Linear regression models were estimated with individual and contextual covariates, along with country-fixed effects. Results indicated that higher policy stringency was associated with increased psychological distress scores and decreased life evaluations. The study also highlighted the role of pandemic intensity (deaths per 100,000 inhabitants) in predicting greater distress and lower life evaluations. Moreover, the negative relationship between policy stringency and life evaluation was mediated by individuals' perceptions of their government's handling of the pandemic. Although strengthened by a large sample size and an extended study period, the results reflected associations rather than causation, and as with all the preceding studies reviewed, pre-pandemic mental health data was not considered.

The remaining studies reviewed instead used both pre- and during-pandemic data on mental health to improve the causal inferences possible for the effects of lockdown and policy stringency on mental health. Firstly, Brodeur *et al.* (2021) circumvented the issue of having no individual-level pre-pandemic data by utilising Google Trends data on the search intensity of thirteen wellbeing-related terms in nine European countries and the United States. Specifically, the authors collated data from 1 January 2019 to 10 April 2020 to estimate changes in wellbeing search terms pre- and during the pandemic. DD, regression discontinuity (RDD), and event study models were estimated, all of which indicated a substantial increase in search intensity for terms related to negative emotions, suggesting potential mental health impacts resulting from lockdown policies. However, an increase in search intensity does not directly reflect realised changes in wellbeing.

Arendt *et al.* (2020) employed a similar strategy to Brodeur *et al.* (2021), but instead used changes in crisis hotline calls during the pandemic in Austria and Germany compared to the same period

in 2019. Data was available from January to the end of March 2020 in Germany, and additionally for April 2020 in Austria. Utilising non-linear regression methods to fit functional forms to the difference in hotline calls in these months in 2020 to the same months in 2019, the study found that hotline calls significantly increased in March 2020, with this increase growing as government restrictions were implemented in both countries. Furthermore, the increases began to decline in Austria, where data was available for April, as announcements were made regarding the lifting of some restrictions. This suggests that the introduction of government restrictions in response to the Covid-19 pandemic placed a significant mental health burden on the populations, although the authors caution that due to the observational and not experimental study design, causality cannot be proven.

Ramiz *et al.* (2021) instead used individual-level longitudinal data from a cohort of French individuals first interviewed in 2014. This cohort was recontacted during the first French lockdown (March to May 2020), resulting in 1,237 responses. The study collected data on self-rated mental and physical health and assessed symptoms of anxiety and depression using the GAD-7 and PHQ-9. It also gathered sociodemographic information and perceptions of COVID-19 and lockdown. Regression models indicated the mean GAD-7 scorers were higher in the lockdown survey, while self-rated health decreased. However, there was no significant difference in the mean PHQ-9 score. Further analysis involved regressing dummy variables reflecting changes in mental health outcomes on sociodemographic variables and perceptions of COVID-19. Findings showed that women, younger adults (aged 23 to 49), the elderly (aged over 70), those living in small spaces (under 30 square meters), and individuals with no access to personal outdoor space were more likely to exhibit increased mental distress during the lockdown. Additionally, those who reported being infected with COVID-19 or experiencing a significant impact on their lives or that of friends and relatives were more likely to exhibit increased mental distress. While this study improved upon previous research by using individual-level pre- and during-pandemic longitudinal data, it faced limitations due to the long period between initial mental health observations and those during lockdown.

Serrano-Alarcon *et al.* (2022) improved further on preceding studies by utilising heterogeneity in the timing of lockdown restrictions being lifted in England and Scotland to employ a DD analysis using one pre- and one during pandemic wave of panel data from the UK Household Longitudinal Study (UKHLS). Specifically, the study examined whether mental health outcomes improved in England after the lockdown eased on May 13, 2020, relative to individuals in Scotland who experienced easing on May 29. The results demonstrated that the easing of lockdown was significantly associated with improved mental health, measured through the GHQ-12. This effect

was especially pronounced among economically disadvantaged individuals. The study conducted several robustness checks, which generally supported these findings. One of the study's strengths was the use of the DD analysis to enhancing causal inference. However, it faced limitations with its identification strategy with a small sample size for the treatment group of Scottish residents, and the fact there was only a two-week difference in policy timings between Scotland and England.

Lastly, Schmidtke *et al.* (2021) used individual-level monthly panel data from the German Job Search Panel (GJSP), collected from December 2018 to December 2020, to estimate the impact of the first and second waves of the pandemic and associated lockdown policies on German workers' mental health. The study employed an event study design, considering 13 March 2020 as the 'event' as this was the day nationwide school and kindergarten closures were implemented. The study used preceding monthly interviews up to the start of 2019 as pre-event observations (a total of 15 observations) and eight monthly interviews until December 2020 as post-event observations, thereby capturing the beginning of the second wave of the pandemic in Germany from October to December 2020. The results indicated that both the first and second waves of the pandemic significantly reduced mental health. However, the impact was smaller during the second wave relative to the first. During the months when infection rates decreased and lockdown restrictions eased, individuals' overall wellbeing returned to pre-pandemic levels. The event-study estimates also suggested that mental health began to respond to rising infection rates before restrictions were implemented, possibly due to anxiety regarding future restrictions. While the event study design illustrated the evolution of mental health during the first year of the COVID-19 pandemic, the study faced limitations, including the absence of an unaffected control group within the data, and a sample limited to German workers which challenges the generalisability of the findings.

3.2 The Big Five Personality Traits and Mental Health

This section reviews the literature on the links between the 'Big Five' personality traits and mental health. We begin by briefly overviewing the history of the Big Five personality traits. Subsequently, we review papers on the general association between the traits and mental health outcomes, some of which consider differential impacts by age and gender. This is followed by an overview of studies which explore factors such as coping behaviours, attributional style, and self-esteem as possible mechanisms linking these association with mental health. Subsequently, studies examining how the mental health effect of adverse events and stressors may vary by personality type. Finally, we explore the current literature on the Big Five personality traits and mental health during the COVID-19 pandemic.

3.2.1 An Overview of the Big Five Personality Traits

3.2.1.1 Defining the Big Five Personality Traits

In the 1940s, Raymond Cattell developed a complex system of 16 primary factors and 8 second-order factors to describe individual differences in personality (Barrick and Mount, 1990; Digman, 1990). However, subsequent attempts to replicate Cattell's work were unsuccessful, leading to the emergence of a five-factor model (Barrick and Mount, 1990). These five dimensions, which closely reflect those used today, were proposed by Tupes and Christal (1961), and popularised by Norman (1963) using the terms 'Extroversion', 'Emotional Stability', 'Agreeableness', 'Conscientiousness', and 'Culture' (Barrick and Mount, 1990; Digman, 1990). These five traits were subsequently dubbed 'Norman's Big Five', although in modern usage 'Culture' has instead been re-termed as 'Openness to Experience' (Barrick and Mount, 1990).

Extroversion reflects an individual's sensitivity to social rewards or their preference towards the outer world (Proto and Zhang, 2021; Staneva *et al.*, 2022). It encompasses sociability, assertiveness, high activity, positive emotions, impulsivity, and a need for stimulation Lucas and Diener, 2001; Shokrkon and Nicoladis, 2021). Introversion can be considered as the opposite of extroversion, with introverts exhibiting low levels of these characteristics and a preference the inner world of subjective experience (Hauner *et al.*, 2008; Staneva *et al.*, 2022).

Emotional stability reflects individuals' emotional sensitivity and resilience to negative emotions (Chaturvedi and Chander, 2010). Emotionally stable individuals exhibit even-tempered responses to challenges and threats, while its converse concept of neuroticism characterises anxiety, self-pity, worry, and proneness to psychological distress (McCrae and John, 1992; Staneva *et al.*, 2022). More neurotic individuals also tend to react poorly to environmental stress and may interpret ordinary situations as threatening (Widiger and Oltmanns, 2017). Agreeableness reflects a tendency towards the maintenance of social stability, with highly agreeable individuals as pro-social or 'other-oriented', whereas those with low agreeableness can be considered as antisocial or 'self-oriented' (Sheese and Graziano, 2004; Proto and Zhang, 2021). More agreeable individuals tend to act cooperatively and hold an optimistic view of human nature (Staneva *et al.*, 2022). Characteristics associated with high agreeableness include compassion, kindness, warmth, selflessness, politeness, trustworthiness, generosity, flexibility, and considerateness (Sheese and Graziono, 2004).

Conscientiousness encompasses an individual's propensity to maintain motivational stability, with more conscientious individuals characterised as organised, responsible, dependable, and self-

disciplined, and preferring planned rather than spontaneous behaviour (Kivimaki *et al.*, 2018; Proto and Zhang, 2021; Staneva *et al.*, 2022).

Finally, openness is the broadest of the Big Five personality traits, however it can generally be considered as reflecting preferences for exploration and new aesthetic, cultural, and intellectual experiences (McCrae, 2004; Proto and Zhang, 2021; Staneva *et al.*, 2022). Highly open individuals are often intellectually curious, open-minded, imaginative, and artistic (McCrae and John, 1992; McCrae and Costa, 2003).

There is an ongoing debate regarding changes in personality traits over the life course. Generally, it is acknowledged that these traits are most variable up until early adulthood, before stabilising later in life (Staneva *et al.*, 2022). However, longitudinal surveys have found detectable shifts in individuals' responses to the questionnaire eliciting the Big Five personality traits over time, even in later life (Boyce *et al.*, 2013). Among these traits, emotional stability and conscientiousness are considered the most age-sensitive (Hale *et al.*, 2023).

3.2.1.2 The Big Five Personality Traits and Economics

Before examining the relationship between the Big Five Personality Traits and Mental Health, we briefly examine the current state of play in the literature linking economics and personality.

Almund *et al.* (2011) and Heckman *et al.* (2019) have provided summaries of empirical economic studies on personality traits predicting life outcomes in areas such as educational attainment and achievement, labour market outcomes, crime, and health. From these studies, the authors outline that of the Big Five personality traits, conscientiousness is the best predictor of overall educational attainment and achievement and a variety of labour market outcomes including overall job performance and wages. Other personality traits have been found to be valued differently across occupations. Conscientiousness has also been found to be one of the most important predictors of criminality alongside agreeableness. All five of the Big Five traits have also been found to predict some health outcomes, however conscientiousness is the most predictive overall. Notably, conscientious has been found to strongly predict longevity, more so than factors such as IQ or socioeconomic status. Openness to experience and agreeableness have also been linked to longer life, whilst conversely neuroticism predicts a short life span. The authors also summarise that neuroticism has been linked to unhealthy behaviours such as tobacco, alcohol, and drug use. Heckman *et al.* (2019) noted that most studies do not address the question of causality, (i.e., do personality traits cause variation in life outcomes or just predict them?), although there are some empirical studies in an educational setting that go further to address this.

To aid in the understanding of how personality and economic outcomes are linked, Ferguson et al. (2011) proposed a framework which combines the study of evolution and biology of personality with an investment model from economics. This framework suggests that external investment or changes in biological systems combined with the influence of thoughts and behaviours can lead to changes in the mean level of an individual's personality trait. Such changes in the mean level of a trait may influence the expression of behaviours associated with that trait, and these changes may feedback into changes in the mean level of the trait. Heckman *et al.* (2019) further provide a model which relates outcomes to personality alongside cognition, other acquired skills, and effort devoted to a task, the latter of which itself is dependent on the other three factors alongside incentives to perform a task and individual preferences. In the model, all personality, cognition, and other acquired skills evolve over time through investment and habituation, and further that investment itself will exhibit a greater influence on different skills at different stages of the life cycle. Both authors advocate for further study into the role of personality traits in determining life outcomes.

3.2.2 Associations between the Big Five Personality Traits and Mental Health

The Big Five personality traits have been strongly linked to mental health disorders by multiple systematic reviews and meta-analyses (Malouff *et al.*, 2005; Hakulinen *et al.*, 2015; Strickhouser *et al.*, 2017; Lyon *et al.*, 2021). These studies consistently identified high neuroticism (low emotional stability) as the most significant predictor of mental disorders in terms of effect size and statistical significance. Conversely, conscientiousness was found to be a consistent predictor of better mental health across all five meta-analyses, while extroversion and agreeableness were found to be negatively associated with mental health disorders in four out of the five studies (Lyon *et al.*, 2021; Malouff *et al.*, 2015; Hakulinen *et al.*, 2015; Kotov *et al.*, 2010), and agreeableness in three out of five (Lyons *et al.*, 2021; Malouff *et al.*, 2015; Strickhouser *et al.*, 2017). Openness was the trait least consistently linked to mental health, with Lyon *et al.* (2021) finding only some components of openness to be negatively associated with anxiety disorders, while the other studies found either it either to not significantly predict mental health (Kotov *et al.*, 2010; Hakulinen *et al.*, 2015; Malouff *et al.*, 2005) or exhibit weaker associations with mental health compared to the other traits (Strickhouser *et al.*, 2017).

Individual-level studies generally confirm these findings from reviews and meta-analyses regarding to neuroticism being the strongest predictor adverse mental health outcomes as well as other measures such as subjective wellbeing (SWB). For instance, Batty *et al.* (2018) analysed longitudinal surveys from the US, UK, and Japan and discovered that higher neuroticism was linked to a 1.3-fold increase in suicide risk, whereas agreeableness was associated with a reduced risk of suicide.

Extroversion, conscientiousness, and openness did not exhibit significant links to suicide risk in their analysis. Correspondingly, McCann (2010) found that high neuroticism could account for 32% of the estimated variance in US state suicide rates in 2004-2005, while low agreeableness could explain 16% of this variance.

Further, Lamers *et al.* (2012) found that neuroticism was the primary correlate of psychopathology among the Big Five personality traits in a sample of 1,161 Dutch individuals, whereas extroversion and agreeableness were associated with emotional and psychological wellbeing. These findings aligned with a 1998 meta-analysis, which identified neuroticism as the most robust predictor of life satisfaction, while extroversion and agreeableness were linked to positive affect (DeNeve and Cooper, 1998). The significance of neuroticism in predicting poorer emotional health was further reinforced by a longitudinal study of 613,397 nationally representative US individuals, where stepwise regressions indicated that 47.5% of the variability in emotional health could be attributed to neuroticism, surpassing other predictors such as socioeconomic status (McCann, 2011). In a subsequent study, Boyce *et al.* (2013) used data from the 2005 and 2009 waves of the HILDA to assess the impact of the Big Five personality traits on life satisfaction. Their fixed-effects first-difference models revealed that neuroticism was negatively associated with life satisfaction, while extroversion, agreeableness, and conscientiousness were positively associated with life satisfaction, with the strength of these associations decreasing in that order. Conversely, openness did not show a significant association with life satisfaction.

Some studies have investigated whether age or gender influences the relationships between the Big Five personality traits and mental health outcomes. For example, Morack *et al.* (2013) examined the influence of the Big Five personality traits on changing perceptions of physical and mental health in old age, using data from ten waves of the HILDA collected between 2001 and 2010. Growth models for physical and mental health were constructed. The results indicated that higher neuroticism was linked to poorer physical and mental health, while higher conscientiousness and extroversion were associated with better physical and mental health. Agreeableness and openness were, respectively, only associated with better and poorer mental health. The surprising result regarding openness was attributed to the possibility that open individuals may expose themselves to more stressful situations due to their inclination for moving forward and achieving personal growth. Further analysis revealed that the associations between personality traits and mental health did not vary by age, except for openness, which exhibited a weaker association with mental health as age increased. In terms of gender, using a US-based sample of 3,032 individuals, Goodwin and Gotlib (2004) found that females scored higher on neuroticism, agreeableness, extroversion, and conscientiousness compared to males, while openness levels were higher in men. Women also had

significantly higher odds of depression than men, with neuroticism playing a significant role in contributing to this gender difference.

Additional studies have explored potential mechanisms linking these personality traits to mental health, including coping strategies (Mirnics *et al.*, 2013; Panayiotou *et al.*, 2014), attributional style (Cheng and Furnham, 2001), and self-esteem (Shi *et al.*, 2015). Mirnics *et al.* (2013) found using Hungarian data that emotional stability had a direct protective effect against psychopathology outcomes. However, the protective effects of extroversion and conscientiousness were significantly mediated by approach and self-regulation coping strategies, with the approach strategy, encompassing positive thinking, a sense of control, coherence, and self-growth, being the strongest of the two. Using Cypriot data, Panayiotou *et al.* (2014) found that active-positive coping, substance use, avoidance, and expression of negative feelings partially mediated the positive relationship between neuroticism and psychological distress, as well as the negative relationship between openness and psychological distress. These coping strategies also fully mediated the relationship between agreeableness and distress. Extroversion and conscientiousness did not show direct or indirect relationships with distress.

Cheng and Furnham (2001) found that attributional style, which reflects how individuals perceive positive and negative life outcomes, mediated the relationships between extroversion and neuroticism with happiness in a sample of British undergraduate students. Specifically, the authors found extroverts exhibited a more optimistic explanatory style in relation to both positive and negative outcomes, which may in turn generate more positive affect following positive events and reduce negative affect following negative events. Conversely, more neurotic individuals tended to have a pessimistic explanatory style after negative outcomes, potentially contributing to increased negative affect. Lastly, in a sample of Chinese medical undergraduate students, Shi *et al.* (2015) found that self-esteem mediated the positive relationship between neuroticism and depression and the negative relationships between agreeableness and openness with depression.

Finally, some studies have explored how personality traits may mediate the impact of negative life events on mental health outcomes, with a particular focus on neuroticism. Kendler *et al.* (2004) found in a longitudinal sample of over 7,500 US-based twins that both neuroticism and experience of adverse events independently increased the risk of depression, with greater neuroticism also significantly increasing the risk of depression following adverse events. Similarly, Ormel *et al.* (2001) found in a small US sample that both neuroticism and stressful life events were associated with the occurrence and reoccurrence of depressive episodes in elderly individuals, with this effect being significantly larger when stressful life events and high neuroticism co-occurred. These

findings were replicated in a longitudinal general population sample, where high neuroticism tended to strengthen the effect of life situation changes and long-term difficulties on psychological distress (Ormel and Wohlfarth, 1991). Bolger and Schilling (1991) also found that neurotic individuals exhibited greater reactivity to minor stressful events, with this reactivity explaining over 40% of the estimated difference in distress between high- and low-neurotic subjects. Furthermore, Mroczek and Almeida (2004) found that daily stress had a greater effect on negative affect for individuals with higher neuroticism in a sample of 1,012 US-based individuals. This mediating effect was more pronounced in older individuals, suggesting that neuroticism heightens reactivity to stressors in older adulthood. However, not all studies have replicated these findings regarding neuroticism. For example, Engelhard *et al.* (2009) found in a sample of US troops interviewed before and during deployment to Iraq that neuroticism did not mediate the observed relationship between adverse events and increases in PTSD or depressive symptoms.

Additionally, there is some evidence linking the other Big Five personality traits to the impact of negative events on mental health outcomes. van der Veen *et al.* (2017) studied a small sample of 333 Dutch individuals who had recently experienced a major depressive episode, finding statistically significant interaction terms between stressful life events and neuroticism, openness, and conscientiousness in their regression models for symptoms of anxiety. Specifically, the results indicated that when a recent life event occurred in the past year, higher neuroticism and openness and lower conscientiousness were associated with greater levels of anxiety. In another small US-based sample, Lockenhoff *et al.* (2009) found that lower baseline extroversion and conscientiousness predicted poorer mental health following extreme adverse life events. However, Spinhoven *et al.* (2011) found that while negative life events independently predicted prolonged experiences of depression in individuals with existing depression disorders, none of the Big Five personality traits moderated this relationship.

3.2.3 The Big Five Personality Traits and Mental Health Responses to the COVID-19 Pandemic

Cross-sectional studies have indicated that the Big 5 personality traits were associated with various mental health outcomes in individuals surveyed during the pandemic. Neuroticism (emotional instability) consistently emerged as being positively (negatively) associated with outcomes including anxiety, depression, and stress from samples across France, China, Canada, Luxembourg, and Croatia (Pauly *et al.*, 2021; Shokrkon and Nicoladis, 2021; Zhang *et al.*, 2021a; Margetic *et al.*, 2022; Michinov and Michinov, 2023). Associations found for the other Big Five traits varied across studies. Extroversion was found to positively predict symptoms of depression and anxiety in

samples with USA and multinational data (Wei, 2020; Nikcevic *et al.*, 2021), but not significantly predict stress and anxiety in a French sample (Michinov and Michinov, 2023). Furthermore, extroversion was negatively associated with aspects of emotional distress in Canadian and Croatian samples (Shokrkon and Nicoladis, 2021; Margetic *et al.*, 2022). Converse relationships were also found for agreeableness, with some studies finding positive associations with emotional distress and symptoms of depression and anxiety (Nikecevic *et al.*, 2021; Margetic *et al.*, 2022), but others finding associations with better mental health (Pauly *et al.*, 2021). Findings for conscientiousness have also varied from being a positive or negative predictor of mental health outcomes across samples (Nikecevic *et al.*, 2021; Margetic *et al.*, 2022; Pauly *et al.*, 2021; Zhang *et al.*, 2021a), whilst openness had either been found to be negatively or non-significantly associated with poorer mental health during the pandemic (Zhang *et al.*, 2021a; Michinov and Michinov, 2023).

All these studies suffer from similar limitations. They utilised non-representative cross-sectional samples on individuals, therefore the estimated relationships simply represented the association between the traits and mental health outcomes at a single point in time during the pandemic. Without pre-pandemic data, the studies are unable to indicate whether the nature of these associations have changed during the pandemic. Furthermore, the studies did not reveal whether the traits moderate the effect of COVID-19 policies on mental health. As such, the causal inferences from these studies are extremely limited. The studies subsequently reviewed address some of these limitations.

Firstly, Zhang *et al.* (2021b) took a novel 'Big Data' approach to estimate the role of openness, conscientiousness, and agreeableness on wellbeing during the early stages of the pandemic. The authors analysed the sentiment of 348,933 tweets posted from 1 April to 24 April 2020, covering 2,231 working adults from across the United States. The authors measured personality using data analytics algorithms to estimate personality characteristics from the history of each users' Twitter profile. They also measured social connectedness using sentiment analysis based on tweets pertaining to family and friends. The severity of the pandemic for each user was calculated using county-level confirmed COVID-19 cases and deaths. Regression based analysis indicated that openness, conscientiousness, and social connectedness were protective factors against the negative wellbeing effect of the pandemic. The authors postulated that this finding for openness may reflect that more open individuals were more acceptive to changes of life induced by the pandemic, treating it as a novel experience. However, the study was limited in the generalisability of its findings, relying on working US-based adults with public Twitter profiles with profile pictures. Furthermore, the study relied on Big Data approaches to estimate individuals' personality traits

rather than explicitly measure them. The analysis also did not measure changes in wellbeing from pre-pandemic levels.

Zhang *et al.* (2023) used pre-pandemic data from the 2018 China Family Panel Study (CFPS) to create a balanced panel of 18,127 individuals who responded to the 2020 CFPS conducted during the pandemic. They authors compared individuals in provinces with lockdowns to those in provinces without lockdowns in China. Using the 8-item CESD to measure depressive symptoms, the authors calculated the differences in responses to each item between the two waves and estimated these differences as a function of provincial lockdown, the Big Five personality traits, and sociodemographic controls. The results indicated that those in lockdown provinces exhibited increased depressive symptoms between 2018 and 2020. Openness and neuroticism were the two significant predictors of depressive symptoms, with openness associated positively and neuroticism negatively with depressive symptoms. This unexpected result for neuroticism was attributed to neurotic individuals potentially having experienced more negative events in the past, thereby potentially being protected by some form of habituation. However, the study does not explore how the traits moderated the impact of provincial lockdown through interaction terms. Instead, the results simply show that openness and neuroticism were significantly associated with changes in depressive symptoms across the entire sample.

Wijngaards *et al.* (2020) instead examined the moderating role of extroversion on the impact of policy stringency on depressive symptoms. The authors hypothesised that extroverts might be at greater risk due to social restrictions inhibiting their urges to seek out social engagement, experience pleasure and excitement, and live in new and exciting surroundings. Conversely, introverts may fare better under stringent measures as they can shamelessly be alone more often and decide when and where to connect with others. The study utilised observations on 93,215 respondents in 47 countries (including 900 from Australia) during the early stages of the pandemic (20 March to 6 April 2020). Country-level heterogeneity in policy stringency was measured by the OxCGRT Stringency Index, with DD models estimated for depressive symptoms controlling for country-level rates and changes in COVID-19 cases and deaths per capita. Converse to many studies, the results showed that higher policy stringency was negatively associated with depressive symptoms, however extreme extroverts exhibited greater depressive symptoms under stringent policy conditions. A key limitation of the study is that the cross-sectional nature of the data precluded the possibility of exploring how the relationship between extroversion and policy stringency may have evolved over time, particularly with countries relaxing and then re-imposing stringent policy measures. The authors postulated that extroverts may have adapted over the course of the pandemic, finding alternative ways to satisfy their needs for social connection.

Equally, the charm of isolation may have waned for introverts with prolonged restriction to social support. The paper also did not explore the role of other personality traits in moderating the impact of policy stringency on mental health.

Addressing these limitations, Zacher and Rudolph (2021) explored whether the Big Five personality traits predicted perceived stressfulness of the COVID-19 pandemic using a longitudinal sample of 588 full-time German employees. Data were collected at six points from April to September 2020, covering the first national lockdown (March to May), easing of restrictions (May to July), and the summer holiday period (July to September). The study estimated latent growth curve models within a structural equation modelling (SEM) framework, which firstly showed that that individuals in the sample exhibited adaption to the pandemic overtime with perceived stress declining more steeply during the early stages of the pandemic (April 2020 to July 2020) than in the subsequent stages (July 2020 to September 2020). The study subsequently found that extroversion was associated higher average levels of perceived stressfulness, with the converse relationship found for emotional stability. The authors then hypothesised that extroversion would be associated with increased stress during lockdown periods and stronger declines in stress when restrictions were eased, whilst more emotionally stable individuals would experience stronger declines in stress during the early pandemic stages and weaker declines in its subsequent stages. Evidence for this hypothesis was found for extroversion but not for emotional stability. None of the other three traits were found to exhibit significant relationships with perceived stress. Taken together, the results imply there was an overall decline in perceived stressfulness of the pandemic, however this was discontinuous in nature between the early stages (April to July) and subsequent stages (July to September) and was conditional on individual differences in extroversion. The authors postulate that extroverted people may have taken longer to adapt to the changes imposed by the pandemic. Although the study is strengthened by having six waves of data, it does not control for pre-pandemic trends. Furthermore, the small sample size of German individuals in full-time employment limits the generalisability of the results.

Staneva *et al.* (2022) improved on previous research by utilising UKHLS panel data providing pre- and during pandemic observations. The sample included over 370,000 person-year observations from 2009 to 2020, including three waves of data collected in April, May, and June 2020 during the pandemic. As the Big Five personality traits were only measured during the third wave of the UKHLS (2011-2013) the authors did not include these as covariates in their models. Instead, they categorised individuals as 'low' (below median) or 'high' (equal to or above median) on each trait and estimated stratified models of psychological distress on an indicator for being interviewed

during the pandemic waves which was interacted with age group. The models were further stratified by gender.

The key findings were as follows. Individuals with high neuroticism were found to exhibit greater positive associations between the pandemic indicators and psychological distress across both men and women, with these differences largest for younger men and older women. Similarly, the estimated positive relationship between the pandemic and psychological distress was greater in the models for extroverts compared to introverts, with this difference most pronounced among young men. The estimated effects of being interviewed during COVID-19 were also found to be higher in the high openness group, whilst those in the low conscientiousness sub-sample were found to exhibit greater increases in psychological distress. Finally, young men and women in with high agreeableness were found to exhibit greater increases in psychological distress during the pandemic, but no differences were found amongst older age groups. However, the study faced several methodological limitations. Firstly, it was forced to assume personality was temporally stable, as the UKHLS only collected information on personality traits at one time point, approximately 10 years before the pandemic. Because of this, the authors only examined differences in personality by stratifying the models rather than introducing interaction terms. This meant individuals were only classified by on one trait at a time, which ignores the fact behaviour can be composed of multiple aspects of personality traits. Furthermore, no statistical tests of difference between the low and high groups for obtained coefficients were conducted. This, combined with the absence of a DD methodology, means causal inferences were not possible.

Proto and Zhang (2021) utilised the UKHLS differently to Staneva *et al.* (2022) by exploiting the fact that individuals tend to be interviewed in the same month in each wave of the UKHLS. As such, they generated a series of balanced panels of individuals providing observations in the months of April, May, June, July, September, and November 2019 and 2020, and January 2020 and 2021. These observations coincided with significant shifts in UK COVID-19 policies, including the initial nationwide lockdown in March 2020, the first easing of restrictions in May 2020, further relaxation in July 2020, a second lockdown in October 2020, its end in December 2020, and the introduction of a third lockdown in January 2021. The study aimed to understand how the Big Five personality traits moderated mental health deterioration during this period using two-period fixed effects regressions for GHQ-12 caseness on the Big Five personality traits interacted with a COVID-19 wave dummy variable. This method allowed for a direct assessment of how personality traits influenced the impact of the pandemic on mental health, whilst also providing indications as to whether these relationships changed over the course of the pandemic.

The key findings were as follows. Agreeableness consistently emerged as a negative predictor of mental health deterioration during the COVID-19 pandemic. In contrast, openness and, to a lesser extent, extraversion, were positive predictors. Neuroticism, surprisingly, did not significantly predict mental health deterioration. The authors posited that this unexpected result could reflect that highly neurotic individuals may have experienced numerous negative shocks in their lives, potentially desensitising them to the pandemic's impact. Furthermore, the study explored variations by gender, race, and ethnicity. Consistent with Staneva *et al.* (2022), females exhibited more significant mental health deterioration during the pandemic compared to males. Heterogeneity analyses revealed some further differences in these relationships. A notable gender difference was observed for the moderating effect of openness, with a large positive effect observed only in the female sample. Among Black, Asian, and Minority Ethnic (BAME) individuals, those with high extraversion or openness experienced greater mental health deterioration than their non-BAME counterparts. Openness negatively predicted mental health deterioration in individuals over 65, while it positively predicted mental health deterioration in younger individuals. Lastly, a negative moderating effect of conscientiousness on mental health deterioration was found only in individuals over 65. Despite these insights, the study still faced limitations. Most notably, the absence of an unaffected contemporaneous control group prevented the use of estimation strategies to enhance causal inference.

3.3 Summary and Contribution to the Literature

The preceding review indicates there was likely an adverse effect of the COVID-19 pandemic on the mental health of Australians, particularly in states enduring extended lockdowns (Czeisler *et al.*, 2021; Fisher *et al.*, 2021; Leach *et al.*, 2023; Butterworth *et al.*, 2022; Li *et al.*, 2023). However, many existing studies suffered from methodological constraints, such as reliance on cross-sectional data or non-nationally representative samples (Czeisler *et al.*, 2021; Fisher *et al.*, 2021; Leach *et al.*, 2023). Among the studies utilising nationally representative HILDA data, one focused solely on a single pandemic wave, examining the mental health of Victorian residents in 2020 (Butterworth *et al.*, 2022), while the other covered extended lockdowns in both 2020 and 2021, but concentrated only on the Greater Capital Cities of each state (Li *et al.*, 2023).

Existing studies also suggest that the Big Five personality traits may play an important role in moderating the impact of lockdown policies on mental health. Evidence suggests that all these traits may be linked to better mental health outcomes, with neuroticism (emotional stability) often demonstrating the strongest association (Malouff *et al.*, 2005; Kotov *et al.*, 2010; Hakulinen *et al.*, 2015; Strickhouser *et al.*, 2017; Lyon *et al.*, 2021; Batty *et al.*, 2018; McCann, 2010; Lamers *et al.*,

2012; DeNeve and Cooper, 1998; McCann, 2011). Some studies proposed these connections may reflect a moderating effect of personality traits between negative events or day-to-day stressors with mental health (Bolger and Schilling, 1991; Ormel and Wohlfarth, 1991; Ormel *et al.*, 2001; Kendler *et al.*, 2004; Mroczek and Almeida, 2004; van der Veen *et al.*, 2017). This possibility had motivated some previous exploration of the Big Five personality traits in shaping mental health during the COVID-19 pandemic.

However, many of these studies have been limited to examining the association between personality traits and mental health using cross-sectional samples collected early in the pandemic. Such studies generally found emotional stability to be linked to better mental health outcomes (Pauly *et al.*, 2021; Shokkron and Nicoladis, 2021; Zhang *et al.*, 2021a; Margetic *et al.*, 2022; Michinov and Michinov, 2023), while the connections between the other four traits and mental health outcomes during the pandemic were less consistent (Wei, 2020; Nikcevic *et al.*, 2021; Shokkron and Nicoladis, 2021; Zhang *et al.*, 2021a; Margetic *et al.*, 2022; Michinov and Michinov, 2023).

Four studies aimed to provide explicit evidence of the moderating role of personality traits during the pandemic (Wijngaards *et al.*, 2020; Zacher and Rudolph, 2021; Staneva *et al.*, 2022; Proto and Zhang, 2021). All identified a negative moderating relationship for extroversion on mental health, but findings concerning the other traits were mixed. Surprisingly, only one of the three studies examining all five personality traits found a significant negative moderating relationship for emotional stability (Zacher and Rudolph, 2021). However, these studies still suffered from methodological limitations, such as small, non-representative samples (Zacher and Rudolph, 2021), a lack of within-sample heterogeneity in COVID-19 policies in monthly samples (Proto and Zhang, 2021), stratification by personality trait rather than estimating interaction effects (Staneva *et al.*, 2022), or relying on cross-sectional multinational policy variation to derive DD estimates for a single time-period (Wijngaards *et al.*, 2020).

In light of these shortcomings, this chapter makes several contributions to the literature. Firstly, it addresses the methodological limitations of prior research on the role of the Big Five personality traits in moderating the mental health effects of the COVID-19 pandemic, whilst also being the first to study this in the Australian context. To this end, we utilised 17 waves of nationally representative individual-level panel data on Australians, including two during-pandemic waves in 2020 and 2021. Australia's state-level COVID-19 policymaking enabled the exploitation of contemporaneous heterogeneity in policy stringency between states to estimate DD models that incorporated the moderating effect of all five personality traits. This enhanced the ability to draw

causal inferences compared to previous studies, which either demonstrated associations between personality traits and mental health using pandemic-era samples (Pauly *et al.*, 2021; Shokkron and Nicoladis, 2021; Zhang *et al.*, 2021a Zhang *et al.*, 2021b; Margetic *et al.*, 2022; Michinov and Michinov, 2023; Zhang *et al.*, 2023) or attempted to estimate moderating effects but were methodologically constrained (Wijngaards *et al.*, 2020; Proto and Zhang, 2021; Zacher and Rudolph, 2021; Staneva *et al.*, 2022).

Furthermore, this chapter investigated how these moderating relationships may have evolved over time during various lockdowns, expanding on existing literature that has examined changes in the moderating effects of personality traits using data from different pandemic months (Zacher and Rudolph, 2021; Proto and Zhang, 2021). Importantly, we employed a more robust methodology to estimate these changes among individuals directly affected by extended lockdowns, rather than merely examining the general evolution of associations between personality traits during different months of the pandemic.

Additionally, this chapter contributes to the broader literature on the impact of lockdown policies on mental health. The methodology employed improved upon many existing studies, which often lacked pre-pandemic data (Garcia-Prado *et al.*, 2022; Adams-Prassl *et al.*, 2022; Toffolutti *et al.*, 2022; Aknin *et al.*, 2022), potentially introducing bias due to the failure to control for pre-pandemic trends (Hale *et al.*, 2023). Furthermore, studies which incorporated pre-pandemic data often relied on less robust mental health measures, such as changes in crisis hotline call volumes or trends in Google searches for mental health terms (Arendt *et al.*, 2020; Brodeur *et al.*, 2021). Those using more rigorous measures with individual-level panel surveys faced challenges such as long gaps between pre-pandemic and during-pandemic observations (Ramiz *et al.*, 2021), non-representative samples (Schmidtke *et al.*, 2021), or relatively weak identification strategies (Serrano-Alarcon *et al.*, 2022).

The nature of our data also allowed for an exploration into how the effects of lockdowns may change over time. In this respect, we extended the only previous study conducted in the Australian context by Li *et al.* (2023) on the effect of the 2020 and 2021 extended lockdowns on mental health by considering not just the Greater State Capitals, but also the Rest of State regions. We also allowed for the estimation of heterogeneous effects not just over time but also by cohort using Wooldridge's (2021) EWTFE estimation method, whilst Li *et al.* (2023) only allowed for the former. Furthermore, Li *et al.* (2023) focussed on the role of green and blue spaces in moderating these effects, paying no attention to personality traits.

Lastly, this chapter adds to the wider literature on how the Big Five personality traits might moderate the effects of negative life events and stressors on mental health This builds on the recommendations of Hale *et al.* (2023) who proposed a theoretical model for the moderating effect of personality traits on mental health as an explanation for both pre- and during-pandemic trends in mental health across Australia, the UK, and US, but did not empirically test this. The COVID-19 pandemic and associated policy restrictions provide an ideal setting to further knowledge in this area as it represented a large-scale, aggregate-level, exogenous shock. This improved on previous studies which have often relied on small samples of individuals self-reporting experienced negative events and stressors (Bolger and Schilling, 1991; Ormel and Wohlfarth, 1991; Ormel *et al.*, 2001; Kendler *et al.*, 2004; Mroczek and Almeida, 2004; van der Veen *et al.*, 2017; Lockenhoff *et al.*, 2009; Engelhard *et al.*, 2009; Spinhoven *et al.*, 2011).

4. Hypotheses

This section outlines the two sets of hypotheses tested in the analysis, which firstly proposed a negative impact of extended lockdown policies on the mental health of Australians, and subsequently outlined the expected moderating effects of the Big Five personality traits.

4.1 The Effect of Extended Lockdowns on Mental Health

Our first hypothesis pertained to the general effect of extended lockdowns on mental health. The preceding review indicated that the extended lockdown implemented in Victoria in the second half of 2020 likely contributed to a decline in residents mental health (Fisher *et al.*, 2021; Leach *et al.*, 2023; Butterworth *et al.*, 2022; Hale *et al.*, 2023). One study provided evidence that the imposition of extended lockdowns in Greater Melbourne, Greater Sydney, and ACT in 2021 also significantly reduced the mental health of residents by a similar magnitude (Li *et al.*, 2023). These findings corroborated a plethora of studies on the mental health impact of lockdown and general COVID-19 policy stringency on mental health from other countries (Garcia-Prado *et al.*, 2022; Adams-Prassl *et al.*, 2022; Toffoulutti *et al.*, 2022; Aknin *et al.*, 2022; Brodeur *et al.*, 2021; Arendt *et al.*, 2020; Ramiz *et al.*, 2021; Serrano-Alacron *et al.*, 2022; Schmidkte *et al.*, 2021; Santomauro *et al.*, 2021). As such, we tested the following as our first hypothesis:

H1: The imposition of extended lockdown caused a larger decline in mental health of affected residents relative to those residing in states which did not implement extended lockdown policies.

4.2 The Moderating Effect of the Big Five Personality Traits

Previous research has explored the relationship between the Big Five personality traits and mental health, suggesting that these traits may moderate individuals' responses to negative events and stressors. Emotional stability consistently emerged as a protective factor for mental health in the face of adversity (Bolger and Schilling, 1991; Ormel and Wohlfarth, 1991; Ormel *et al.*, 2001; Kendler *et al.*, 2004; Mroczek and Almeida, 2004; van der Veen *et al.*, 2017; Lockenhoff *et al.*, 2009). Cross-sectional studies conducted during the pandemic reinforced these findings, with emotional stability consistently found to be associated with better mental health (Pauly *et al.*, 2021; Shokkron and Nicoladis, 2021; Zhang *et al.*, 2021a; Margetic *et al.*, 2022; Michinov and Michinov, 2023). However, the associations between the other four personality traits and mental health outcomes during the pandemic were less clear (Wei, 2020; Nikcevic *et al.*, 2021; Shokkron and Nicoladis, 2021; Zhang *et al.*, 2021a; Margetic *et al.*, 2022; Michinov and Michinov, 2023).

Studies explicitly examining the moderating effects of the Big Five personality traits during the COVID-19 pandemic also yielded conflicting findings (Wijngaards *et al.*, 2020; Zacher and

Rudolph, 2021; Staneva *et al.*, 2022; Proto and Zhang, 2021). All four of these studies found that extroverts tended to experience poorer mental health during the pandemic. However, of the three studies exploring all five personality traits, only one identified a protective moderating effect for emotional stability (Zacher and Rudolph, 2021), while two suggested a protective effect for agreeableness and a negative moderating relationship between openness and better mental health (Proto and Zhang, 2021; Staneva *et al.*, 2022). Conversely, findings regarding conscientiousness were inconsistent, ranging from weakly negative, to positive, to non-significant (Proto and Zhang, 2021; Staneva *et al.*, 2022; Zacher and Rudolph, 2021). Various mechanisms may explain these inconsistent findings for each of the five traits.

Extroverts might initially suffer more under lockdown conditions due to restrictions inhibiting their need for social interactions (Zacher and Rudolph, 2021; Staneva, 2022), although this may diminish over time as they adapt to alternative means of maintaining social connections (Proto and Zhang, 2021). Conversely, extroverts tend to adjust better to sudden life events, and generally exhibit more positive affect and retain this longer than introverts in the face of stressful situations (Li *et al.*, 2021; Shokrkon and Nicoladis, 2022; Staneva *et al.*, 2022).

Emotional stability would likely offer protection against the adverse effects of extended lockdowns due to its association with resilience and effective coping strategies. In contrast, neuroticism, the converse of emotional stability, reflects a higher sensitivity to negative emotions when facing adverse events and threats, and has also been linked to negative coping behaviours such as substance use and avoidance (Zacher and Rudolph, 2021; Proto and Zhang, 2021; Mirnics *et al.*, 2013). However, it is possible that neurotic individuals may not be as susceptible to poorer mental health as this suggests, since neurotic individuals tend to already have experienced negative events in the past and therefore may exhibit some form of habituation (Proto and Zhang, 2021).

Conscientiousness would also be expected to provide a protective moderating effect due to its association with motivational stability, self-discipline, and persistence, which may help individuals overcome practical constraints associated with lockdown policies and manage negative emotions (Proto and Zhang, 2021; Staneva *et al.*, 2022). However, more conscientious individuals exhibit a preference for long-term planning, which could be significantly constrained during periods of extended lockdowns (Proto and Zhang, 2021).

Conflicting mechanisms may also be considered for the role of agreeableness. On the one hand, we might expect a protective effect for more agreeable individuals due to their inclination toward maintaining social stability and pro-social attitudes (Proto and Zhang, 2021). As such, more agreeable individuals may view lockdown as something that is necessary for the 'greater good'.

Agreeableness is also linked to active coping behaviours which can promote positive affect (Li *et al.*, 2021; Staneva *et al.*, 2022). However, given that extended lockdowns often occurred in response to higher COVID-19 cases and death rates, highly agreeable individuals might experience negative mental health effects from knowing about the suffering of others (Proto and Zhang, 2021).

Finally, openness would likely accentuate the mental health impact of lockdowns, as more open individuals prefer exploration and new experiences (Proto and Zhang, 2021). However, because openness encompasses a broad range of traits, including intellectual curiosity, imagination, and artistry, individuals with this trait might find creative ways to adapt to lockdowns or view them as novel opportunities for personal growth (McCrae and John, 1992; McCrae and Costa, 2003; McCrae, 2004; Proto and Zhang, 2021; Zhang *et al.*, 2021b; Staneva *et al.*, 2022;).

Considering these mechanisms against the predominant findings from the literature, we proposed the following two-part hypothesis.

H2a: Higher extroversion and openness increased the negative mental health effect of extended lockdowns.

H2b: Higher emotionally stability, conscientiousness and agreeableness reduced the negative mental health effect of extended lockdowns.

5. Data and Descriptive Statistics

This section begins by providing details of the data used to test the hypotheses specified in Section 4. This includes an overview of the Household, Income, and Labour Dynamics Australia (HILDA) survey, followed by a description of the information it provides on mental health and wellbeing, personality, regions and dates of interview, and socioeconomic and demographic characteristics. Subsequently, we provide an overview of the Oxford COVID-19 Government Response Tracker (OxCGRT) dataset and how this can be used conjunction with the HILDA. Detailed information on how we utilised the information in both datasets to construct the variables used in our analysis is provided Table A1 in Appendix 3A. Subsequently, we present descriptive statistics for the sample.

5.1 The Household, Income, and Labour Dynamics Australia (HILDA) Survey

5.1.1 Overview of the HILDA

The HILDA is an annual, longitudinal, nationally representative household panel survey. The first wave of data was collected in 2001, successfully interviewing 19,914 individuals from 7,682 households. The sample was replenished in its 11th wave (2011) with an additional 5,462 individuals from 2,153 households added. Wave 21 is the latest release, which surveyed 22,434 individuals from 9,358 households in 2021 (Summerfield *et al.*, 2021).

The survey collects a wide range of socioeconomic and demographic information on individuals at both the individual and household level. The data are derived from three questionnaires: the 'Household Questionnaire' (HQ), the 'Person Questionnaire' (PQ), and the 'Self-Completion Questionnaire' (SCQ). One member of the household is interviewed for the HQ, which elicits information on childcare arrangements, housing, household spending, and household wealth. The PQs are administered to each member of the household aged 15 years and above. In every PQ, individuals provide information on their education, employment status, income, family formation, relationships, and health. Special additional topics are sometimes administered on areas such as wealth, further health (including personality traits), retirement, and literacy and numeracy. In wave 20, an additional module was introduced on COVID-19 with topics pertaining to infection and perceived impact of the pandemic. Some of these questions were retained in wave 21. Finally, the SCQ is administered separately, and may be completed before or after the interview date. The purpose of the SCQ is to cover topics which individuals may not have felt comfortable answering face-to-face, such as mental health and wellbeing, attitudes and values, and job or workplace issues (Summerfield *et al.*, 2021).

In the pre-pandemic waves of the data (1-19), all HQ and PQ interviews were conducted face-to-face. In wave 20, these face-to-face interviews were replaced by telephone interviews due to the pandemic. Despite these changes, there was only a small reduction of 1.5% in re-interview rates between waves 19 and 20 (Watson *et al.*, 2021). For wave 21, telephone interviews predominantly continued given the rises in COVID-19 cases in NSW, Victoria, and ACT (Summerfield *et al.*, 2021). There was a small reduction in the re-interview rate of 1.2% (Watson *et al.*, 2022).

5.1.2 Mental Health in the HILDA

The HILDA administers numerous measures pertaining to mental health and wellbeing to participants in the SCQ. In this study we utilised the five-item Mental Health Inventory (MHI-5), which is derived from the 36-item Short Form Survey (SF-36). This was administered in all 21 waves of the HILDA.

The MHI-5 reflects symptoms pertaining to depression and anxiety, and measures of positive affect (Butterworth and Crosier, 2004). Itis derived by asking individuals how much time in the past four weeks: "Have you been a nervous person?", "Have you felt so down in the dumps that nothing could cheer you up?", "Have you felt calm and peaceful?", "Have you felt downhearted and blue?", and "Have you been a happy person?". Responses were on a 6-point Likert scale from "All of the time" (=1) to "None of the time" (=6). Responses can then be summed, with items 2 and 5 reverse coded, to produce a total score of from 5 to 30 with higher scored reflecting better mental health. This score can then be transformed onto a scale from 0 to 100 through standard linear transformation (Ware *et al.*, 2002). This process is performed by the HILDA authors, and the score is available in the data release. The MHI-5 demonstrates adequate criterion and construct validity (Friedman and Delavan, 2005) and shows comparable psychometric performance to similar measures such as the General Health Questionnaire (GHQ-12) (McCabe *et al.*, 1996).

5.1.2 The 'Big Five' Personality Traits Variables

Wave 5 of the HILDA administered the Five Factor Personality Inventory for the first time. The inventory consists of 36 questions, with each question rated on a 7-point scale from "Does not describe me well" (=1) to "Describes me very well" (=7). The traits of extroversion, emotional stability, agreeableness, conscientiousness, and openness are measured from various items on the inventory, with an index constructed on a continuous scale of 1 to 7 reflecting the mean score pertaining to the relevant items for each trait. For extroversion, the items are: 'Talkative', 'Bashful' (reverse scored), 'Quiet' (reverse scored), 'Shy' (reverse scored), 'Lively', and 'Extroverted'. For emotional stability, the items are: 'Envious', 'Moody', 'Touchy', 'Jealous', 'Temperamental', and 'Fretful' (all reverse scored). For agreeableness, the items are: 'Sympathetic', 'Kind', 'Cooperative',

and 'Warm'. For conscientiousness, the items are: 'Orderly', 'Systematic', 'Inefficient' (reverse scored', 'Sloppy' (reversed scored), 'Disorganised' (reverse scored), and 'Efficient'. Finally, for openness, the items are: 'Deep', 'Philosophical', 'Creative', 'Intellectual', 'Complex', and 'Imaginative'.

The personality indices constructed in the HILDA have been shown to have adequate levels of normality, construct validity, internal consistency, and external correlates (Losconz *et al.*, 2009). For ease of interpretation, we re-scaled each personality variable to a scale of 0 to 1 so that a unit change reflects the difference between the extremes of each trait.

5.1.3 Region and Timing of Interview

The unrestricted access HILDA data provides information on a household's location at the Greater Capital City Statistical Area (GCCSA) level. There are 16 GCCSA regions which cover the whole of Australia without gaps or overlaps. The GCCSAs were designed to provide a consistent boundary reflecting the functional extent of each state/territory capital city (Australian Bureau of Statistics, 2012). These boundaries were last updated in 2021.

The HILDA data provides the following geographical boundaries based on the GCCSAs. Victoria is divided into Greater Melbourne and Rest of Victoria; New South Wales (NSW) is divided into Greater Sydney and Rest of NSW; Queensland is divided into Greater Brisbane and Rest of Queensland; South Australia (SA) is divided into Greater Adelaide and Rest of SA; and Western Australia (WA) is divided into Greater Perth and Rest of WA. Although Northern Territory (NT) and Tasmania are also divided into the Greater State/Territory Capital (Darwin and Hobart) and Rest of State/Territory by the Australian Bureau of Statistics (ABS), in the unrestricted HILDA data information on residents in NT and Tasmania is only available as the entire state/territory region. Finally, Australian Capital Territory (ACT) is only classified as one GCCSA by the ABS, whilst individuals from the 16th GCCSA for Other Territories (including Jervis Bay, Christmas Island, and Cocos Islands) are not surveyed by the HILDA. Thus, in our data we had a total of 13 geographical region indicators. This level of delineation between geographical regions was sufficient for our study.

The data also provides information of the date of completion of three questionnaires. We used the SCQ completion date as since the SCQ elicited mental health. Using this information in conjunction with the region indicators allowed for the assignment of extended lockdown indicators to individuals. We provide details of our precise identification strategy in Section 6, where we differentiate between states which implemented extended lockdowns (Victoria, NSW, and ACT) and those which did not (Queensland, SA, WA, NT, and Tasmania).

5.1.4 Socioeconomic and Demographic Information

The HILDA collects a wide range of socioeconomic and demographic information on respondents. We report on the information which is most relevant to our study based on the existing literature on the determinants of mental health, particularly from studies which utilised the HILDA or conducted analyses on mental health during the COVID-19 pandemic (Butterworth *et al.*, 2022; Li *et al.*, 2023).

Relevant individual-level information included gender, age, educational attainment, marital status, labour force status, smoking behaviour, alcohol consumption, self-rated health, long-term health conditions, frequency of social interaction with friends or relatives, social support, self-rated financial status, experience of negative life evens, and the individuals' relationship within their household.

Relevant household-level characteristics included the number of child (under 15 years old) and adult household members, dwelling type, real household annual disposable income per household member[8] (which we adjusted to April 2022 prices using quarterly CPI data[9]), remoteness area, and decile of the household in the Socioeconomic Indexes for Areas (SEIFA) Index of Relative Socioeconomic Advantage and Disadvantage (IRSAD).

This information was used to control for individual- and household-level characteristics in analysis. Table A1 provides greater details how we used this information to construct the variables used in our analysis.

5.2 The Oxford COVID-19 Government Response Tracker (OxCGRT)

The OxCGRT is an open-access dataset which provides a systematic and comparable record of government responses to COVID-19 (Hale *et al.*, 2021). It provides daily policy data from 1 January 2020 to 31 December 2022, alongside a record of total COVID-19 deaths and cases. A total of 25 policy indicators are provided across five groups: 'Closure and containment indicators', measuring restrictive policies such as gathering limitations, work and school place closures, and travel restrictions; 'Economic indicators', measuring policies such as financial support and debt relief; 'Health indicators', measuring policies such as mask mandates and contact tracing; 'Vaccine indicators', measuring policies such as vaccine mandates and prioritised groups; and

[8] Disposable income is a derived variable available in the HILDA data which is calculated as total income after receipt of government benefits and deduction of income tax (Summerfield *et al.*, 2022).

[9] Available from: https://fred.stlouisfed.org/tags/series?t=australia%3Bcpi

'Miscellaneous', for policies identified which do not fall into the other four categories. Each of the 25 indicators has a minimum score of 0 (absence of policy), with varying maximum scores of 3, 4, or 5 representing the strongest level of policy. This information is aggregated into four policy indices: the Government Response Index, Stringency Index, Containment and Health Index, and Economic Support Index. The Stringency Index was the most relevant for this study. It is constructed from 9 indicators (all 8 of the 'Closure and containment indicators' plus 1 of the 'Health indicators'). The constructed index[10] is on a normalised continuous scale from 0 (least stringent) to 100 (most stringent).

For Australia, the data are available at the country-, state-, or within-state- (Greater State Capital and Rest of State) level[11]. At the within-state-level, six versions are available for each index. The most relevant of these for our purpose are the 'State Total' and 'City Total' levels. The 'State Total' level describes the overall policy environment applying to residents of the state, inclusive of any policies set by the national government which may be more stringent than those set by the state themselves. Thus, there is a daily state total index for each of the eight states. The 'City Total' level describes the overall policy environment which applies to residents on the city, inclusive of any national or state level policies applicable to residents of the city which are more stringent than those set by the city-level government. For Australia, the city level is defined by the Greater State Capital and Rest of State area. As such, we matched the stringency index to individuals in the HILDA based on their GCCSA and date of interview. As noted above, for Tasmania and NT, the HILDA only distinguishes individuals at the state-level, therefore they were assigned the 'State Total' index, as were residents of ACT which encompasses a single GCCSA. For the remaining states, the 'City Total' index used, meaning individuals from the two within-state GCCSAs were assigned different values. Cumulative recorded COVID-19 cases and deaths are also available in the Australian OxCGRT data. These are calculated at the state level and were assigned as such to individuals in the HILDA. For all observations preceding 1 January 2020, the stringency indices, deaths, and cases were set to zero.

5.3 Data Cleaning and Sample Selection

Waves 1 to 21 of the HILDA provided 321,692 observations on individuals aged 15 years or above. As personality is not measured until wave 5, we firstly dropped all observations on individuals

[10] For full details on the construction of the index see Hale *et al.* (2021).

[11] The details provided in this paragraph on the Australian OxCGRT are obtained from the Australia Covid Policy github repository available at: https://github.com/OxCGRT/Australia-covid-policy/blob/main/README.md

from waves 1 to 4, removing 52,146 observations. Subsequently, we dropped all individuals who did not return an SCQ (which, amongst other information, contains the SF36 used to derive the MHI-5). This removed 26,325 observations, which corresponds with the average non-response rate to the SCQ across all HILDA waves of 10%[12]. Watson *et al.* (2022) showed that non-response rate to the SCQ in the HILDA was associated with individual-level characteristics of being male, having lower education, being in full-time employment, and living with a long-term health condition. Household-level characteristics associated with SCQ non-response were living with children under 15, living in Sydney, Melbourne, or remote areas, and living in rental accommodation. As such, the sample may not be truly nationally representative.

In the HILDA, missing or invalid responses are indicated by negative numbers representing the various reasons for missingness (Summerfield *et al.*, 2021). We set all negative values indicating missingness to equal to missing. We subsequently dropped 1,346 (0.58%) observations with missing MHI-5 data, leaving 229,116 observations. In the HILDA, disposable income can take negative values, which mainly results from individuals whose income is derived from business who reported losses. Consistent with other studies using the HILDA, we set 417 observations with negative real household disposable income per capita to missing (La Cava and Simon, 2003), and then winsorised the 1% tails to remove outliers.

For the analytical sample, we only utilised individuals with complete information on personality and the relevant individual- and household-level characteristics in a given wave. This comprised 190,995 observations. Finally, we excluded 3,811 singleton observations from the analytical sample, as their inclusion in our models may overstate the statistical significance of the coefficients thereby leading to possibly incorrect inference (Correia, 2015). This provided a final baseline analytical sample of 187,074 observations on individuals across 17 waves.

To explore the impact of missingness we conducted independent sample *t* tests between those individuals included in the analytical sample and those excluded due to missing observations on one or more of the variables utilised in the baseline analytical models. The results from this are presented in Table F1 in Appendix 3F.

Table F1 indicates that missingness in the sample was unlikely to be missing completely at random (MCAR), since missingness appeared to be related to observed characteristics (Mack *et al.*, 2018). Briefly, those included in the analytical sample exhibited somewhat better MHI-5 scores, and were

[12] See Table 2.2. in the HILDA Survey User Manual for the wave 21 release (Summerfield *et al.*, 2021, p.13)

slightly less extroverted and slightly more emotionally stable, agreeable, conscientious, and open. Men were somewhat less prevalent in the analytical sample, and those with complete case were more likely to be older, better educated, in employment, and have higher household income. Regarding marital status, married individuals were significantly more likely to be included in the analytical sample, whilst conversely those who had never married were significantly more likely to have incomplete data. Those with complete cases were more likely to be smokers but less likely to be weekly drinkers, whilst missingness also decreases with self-rated health and with level of social support. Although differences were found between different frequencies of interactions, these did not appear to be systematic; this also applied to self-rated financial status levels. Those included in the analytical sample were also less likely to report experiencing recent negative life events. Both adult and child household size were slightly smaller in the analytical sample, with complete cases more frequently being found for those in couples and less frequently found for single persons, dependent students, and other family or unrelated household members. Those in the analytical sample were also more likely to reside in separate (detached) housing relative to other dwelling types and were also somewhat more likely to be of a higher IRSAD decile. Finally, missingness was greater for those living in outer regional, remote, or very remote Australia. As missingness appears related to several observable characteristics of participants, it is likely that our data is missing at random (MAR).

5.4 Descriptive Statistics

5.4.1 Baseline Sample

Table 5.1 provides the descriptive statistics of the baseline sample consisting of 187,074 observations on individuals with non-missing MHI-5, personality, and socioeconomic and demographic variables. We also provide descriptive statistics for the alternative mental health and wellbeing measures and the OxCGRT variables for individuals present in the baseline sample.

The mean MHI-5 score in the sample was 73.813, indicating on average the sample was in relatively good mental health. This is comparable to the mean score of the sample of HILDA individuals from just the State Capital Cities utilised by Li *et al.* (2023).

Next, the highest (normalised) mean score on all five personality traits was for agreeableness (0.700), whilst the lowest was for openness (0.536). Mean extroversion score was 0.570, indicating on average individuals in the sample were slightly more extroverted than introverted. The mean emotional stability score was 0.700, showing that our sample tended towards emotional stability. Finally, the mean conscientiousness score in the sample was 0.685. These scores for all traits were

slightly smaller than those exhibited by individuals in the UKHLS sample utilised by Proto and Zhang (2021).

For a more meaningful presentation of the OxCGRT Stringency Index and COVID-19 deaths and cases, we present descriptive statistics only for waves 20 and 21. The mean Stringency Index score was 68.496. The maximum was 96.300, recorded in Adelaide and the Rest of SA the Rest of SA between 20 July to 27 July 2021. Mean COVID-19 cumulative state-level deaths and cases were 213.705 and 15,086 respectively. The maximum state deaths recorded was 2,675 observed in Victoria on 18 March 2022, with the maximum recorded state cases of 1,435,768 observed in NSW on 10 March 2022.

Regarding the geographical distribution of responses, Greater Melbourne and Greater Sydney provided the most observations (17.6% and 15.6% respectively), whilst the fewest were from NT (0.7%). The distribution of responses across States and Territories were broadly reflective of the distribution of the Australian population, whereby NSW is the most populous state, followed by Victoria, Queensland, WA, SA, Tasmania, ACT, and NT. Correspondingly for remoteness area classifications, 65.9% of observations were on individuals residing in a 'Major City of Australia', 22.5% on individuals residing in 'Inner Regional Australia', 10.3% on individuals residing in 'Outer Regional Australia', and 1.4% on individuals residing in 'Remote or Very Remote Australia'.

For individual-level demographics, 46.4% of the sample were male, whilst 74.2% of the sample had completed year 12 education or above. In the age groups, the fewest observations were from the youngest age group of 15- to 24-year-olds (13.4%) and the greater from the oldest age group of those aged 65 years old and over (18.3%). Mean age in the sample was 46.389. The majority of individuals in the sample were married (52.1%), followed by never married (20.4%), in a 'de facto' relationship (14.3%), divorced (6.3%), widowed (4.3%), and separated (2.5%). The mean unemployment rate was 3.1%, which is slightly below the average rate for the period of 2005 to 2022 (5.55%) (World Bank, 2023), although this rate is consistent with that found in Li *et al.* (2023). Approximately 17.1% of the sample were weekly smokers, whilst 46.7% stated they consumed alcohol at least once per week. Most individuals rated their health as 'good' (36.5%), followed by 'very good' (35.8%), 'fair' (13.8%), 'excellent' (10.7%), and 'poor' (3.1%). Further, 28.5% of the sample indicated they had a long-term health condition that impacted their daily lives. Mean social support index score was 54.357, indicating on average individuals in the sample felt they had relatively high social support. The most commonly reported frequency of social interaction with friends or family outside of the household was 'About once a week' (31.4%), whilst approximately

18.8% of the sample indicated they had such interaction less frequently than once a month. Finally, 38.9% of the sample reported experiencing a negative life event in the past 12 months.

At the household level, the most prevalent family relationship was a couple under 65 years old without children under 15 years old (29.3%), followed by a couple with children under 15 years old (24.7%). The least frequent family relationship type was being unrelated to all household members (1.0%). The mean adult household size was 2.276, whilst the mean child household size was 0.562. The mean real annual monthly disposable income per capita in the sample was 29,100 AUD (in April 2022 prices), whilst the most prevalent self-assessment of household finances was 'Reasonably comfortable' (53.4%). Finally, the most prevalent dwelling type was a 'Separate House' (82.2%), followed by 'Flat' (10.4%), 'Semi-detached/Terrace/Townhouse' (6.7%), and finally 'Other' (0.7%).

5.4.2 Mean MHI-5 Score by Extended Lockdown Cohorts

Figure 5.1 provides the mean MHI-5 scores from wave 5 to wave 21. We stratified this based on state-level cohorts defined by the lockdown policies pursued by the states following the lifting of national lockdown guidelines. Specifically, we plotted the mean MHI-scores for Victoria, where extended lockdowns were implemented in 2020 and 2021, the states of NSW and ACT (combined), where extended lockdowns were implemented in 2021 only, and the rest of Australia (combined) where no extended lockdowns were implemented in 2020 and 2021 (beyond the initial national lockdown). The figure firstly indicates that mean MHI-5 scores fell across all cohorts between waves 19 and 20 following the start of the pandemic. However, this decline was significantly larger for residents of Victoria. Subsequently, mean MHI-5 score fell again in Victoria in 2021, whilst NSW and ACT also experienced a sharp decline. Meanwhile, the rest of Australia exhibited only a marginal decline in mean MHI-5 score between waves 20 and 21. This provides preliminary evidence for our first hypothesis that the implementation of extended lockdowns caused a larger decline in mental health of affected residents compared to those residing in states which did not pursue this policy.

5.4.3 OxCGRT Stringency Index by State

Figures 5.2 and 5.3 provide the daily OxCGRT Stringency Index values for the period 1 January 2020 to 28 March 2022 for states which did and did not pursue extended lockdown policies respectively. We can see across the two figures that between January and June 2020, all states had similar stringency levels, with a rapid increase in March 2020 as national stay-at-home guidelines were implemented, and a subsequent fall as all states lifted these restrictions around May 2020. In Figure 5.2, we see the stringency index rose significantly from July 2020 for the state of Victoria

and remained elevated until October 2020. Conversely, in NSW and ACT the stringency index remained relatively constant or fell during this period, as was the case for the states depicted in Figure 5.3. This clearly reflects the differential policy of Victoria relative to all other states in 2020. From 2021, the difference in policy approach between the states which implemented extended lockdowns and the states which implemented snap lockdowns is clear. In Figure 5.3, we observe short, sharp spikes in stringency corresponding to these snap lockdowns, whilst in Figure 5.2 we observe from July 2021 all three states exhibited an extended period of high stringency corresponding to the extended lockdowns.

6. Baseline Specification and Estimation

This section provides the baseline specification and estimation methods utilised to test the hypotheses specified in Section 4. It begins by outlining the identification strategy we utilised to construct our treatment group for extended lockdowns. Subsequently, we present our baseline specification, whereby we first outline a general model of mental health as a function of extended lockdown, personality, and other socioeconomic and demographic variables. We then discuss estimation strategies which allow for the differential timing of extended lockdowns across states to be accounted for in estimation. This is followed by a presentation of the baseline estimation strategy we utilised for the analysis, the so-called 'Extended' two-way fixed effects (ETWFE) estimator (Wooldridge, 2021). Finally, we present the robustness checks we employed.

6.1 Identification Strategy

We employed the following identification strategy to define the extended lockdown cohorts used in our analysis. We firstly defined all individuals as pre-COVID-19 when surveyed in waves 1 to 19 (*i.e.*, 2001 to 2019). We then defined extended lockdown as our treatment variable for our analysis for waves 20 and 21, with individuals assigned to this treatment group based on the dates of lockdowns within each region and the date of completion the SCQ containing the MHI-5 measure. A summary of the information below is provided in Table B1 in Appendix 3B, showing the dates of lockdowns within Victoria, NSW, and ACT and the proportion of SCQs returned within these dates.

In 2020, all Australian states followed national lockdown orders from the end of March, with all states lifting these orders by early May (Butterworth *et al.*, 2022). This was prior to HILDA wave 20 data collection. On 1 July 2020, 10 postcodes within Greater Melbourne were placed under lockdown, applying to approximately 311,000 residents (Australian Government. Department of Health and Aged Care, 2020). A further two postcodes were added to this on 4 July, with the whole of Greater Melbourne then placed under lockdown from 9 July (Blakely *et al.*, 2022), which we used at the start date for the extended lockdown. On 2 August, a 'State of Disaster' was declared in Greater Melbourne, implementing a curfew alongside existing lockdown restrictions. The Rest of Victoria was also placed under lockdown without curfew (Victoria State Government. Health and Human Services, 2020a). Lockdown conditions were lifted in the Rest of Victoria from 18 October 2020 and on 28 October in Greater Melbourne (Victoria State Government. Health and Human Services, 2020b). The main period of data collection for wave 20 of the HILDA took place in August, September, and October 2020 (Summerfield *et al.*, 2021). As such, 96% of SCQs were completed by residents of Greater Melbourne during extended lockdown, whilst this figure was

90% for the Rest of Victoria. Hence, in our baseline analysis, we defined all residents of Victoria observed in wave 20 as being 'treated' by extended lockdown.

In 2021, three states implemented extended lockdowns (Victoria, NSW, and ACT), whilst the remaining states employed only 'snap' lockdowns lasting no more than one to two weeks (Edwards *et al.*, 2022). Whilst Victoria initially implemented a series of state-wide snap lockdowns in February, May, and July 2021, on 5 August an extended state-wide lockdown was implemented (Premier of Victoria, 2021a; Victoria State Government. Health and Human Services, 2021; Premier of Victoria, 2021b; Australia Bureau of Statistics 2021). This was lifted on 10 September for the Rest of Victoria (excluding Shepparton); however, some areas were subsequently placed under snap-lockdowns, the last of which was lifted on 8 October 2021. The Greater Melbourne lockdown was subsequently lifted on 22 October 2021 (Australia Bureau of Statistics, 2021). Again, HILDA data collection primarily took place during August, September, and October 2021 (Summerfield *et al.*, 2021).

Besides a snap-lockdown for the Northern Beaches area of Sydney between late December 2020 and early January 2021, NSW did not implement any form of lockdown until 26 June 2021, when Greater Sydney was placed under an extended lockdown (The Guardian, 2021; Reuters, 2021). On 14 August 2021, restrictions were extended state-wide (NSW Government. NSW Health, 2021a). The state-wide lockdown ended on 11 September 2021, but for continued for a further month in Greater Sydney (BBC News, 2021). Furthermore, numerous local government areas (LGAs) across the Rest of NSW which exhibited higher rates of transmission after 11 September were subsequently placed back into lockdown until October (NSW Government. NSW Health, 2021b).

Finally, the government of ACT had not implemented any lockdowns since the lifting of national lockdown in May 2020 (Edwards *et al.*, 2022). However, on 12 August 2021, the entire territory was entered into an into a lockdown which ultimately lasted until 14 October 2021 (Legal Aid ACT, 2021; ACT Government, 2021).

To avoid complications arising due to non-absorbing treatment, we defined all residents of Victoria, NSW, and ACT as treated by extended lockdown in 2021. This provided observations on 8,435 individuals. A total of 1,868 (22%) individuals were observed outside of lockdown, of which 962 (11%) were observed 'pre-lockdown' and 906 (11%) 'post-lockdown'. However, these figures do not account for some regions in the Rest of State areas re-entering lockdown after initially being lifted. Furthermore, although we imposed a strict cut-off for the post-lockdown dates, the MHI-5 asked individuals to consider how they felt in the past 4 weeks. As such, we

believe it was reasonable to define all individuals in Victoria, NSW, and ACT as 'treated' by extended lockdown in 2021.

Thus, in our baseline analysis, all residents of Victoria interviewed in wave 20 were considered treated, and in wave 21 all residents across Victoria, NSW, and ACT interviewed were considered treated. Robustness tests were conducted addressing the assumptions of this identification strategy.

6.2 Baseline Specification

To test our hypotheses, we modelled mental health as a function of extended lockdown, socioeconomic and demographic characteristics, and region and time fixed effects. A general specification for this model is given by *Equation (1).*

Equation (1)

$$MHI_{it} = \alpha + \beta_1 Lockdown_{it} + \mathbf{X_{it}}\boldsymbol{\beta} + \mu_t + \mu_c + \varepsilon_{it} + \varepsilon_i$$

Where i indexes individuals, t indexes wave, and c indexes GCCSA. Thus, *Equation (1)* specifies that the MHI-5 score of an individual i during wave t (MHI_{it}), was a function of a binary variable indicating the individual was observed under lockdown at time *t* ($Lockdown_{it}$), socioeconomic and demographic characteristics (including personality traits) contained in the vector $\mathbf{X_{it}}$, time-fixed effects μ_t, GCCSA fixed effects (μ_c), a time-varying individual error component (ε_{it}), and a time-invariant individual error component (ε_i). As per *H1*, the expected direction of β_1 is negative. The controls variables included the vector $\mathbf{X_{it}}$ were selected primarily from those utilised by Li *et al.* (2023), as well as other studies reviewed using Australian data (Czeisler *et al.*, 2021; Fisher *et al.*, 2021; Butterworth *et al.*, 2022; Leach *et al.*, 2023).

Briefly, the vector $\mathbf{X_{it}}$ firstly contained the Big Five personality traits, which were normalised on a scale of 0 to 1. Individual-level controls included an indicator for an individual being male, a series of indicators for age category from 25-34 years old to 65 years old and above were included (with 15–24-year-olds excluded as the reference category), indicators for individuals who were unemployed and not economically active (with employed as the reference category), indicators for the individual being a weekly smoker and weekly drinker of alcohol, indicators for self-rated health measured on a five-point scale from "Very poor" to "Excellent" (with the former omitted as the reference category), and an indicator for an individual reporting they have a long-term health condition. We further included a binary variable capturing whether the individual had reported experiencing any negative life events in the past year. Measures of social support were also included, firstly through a social support index, and second through self-reported frequencies of

interaction with friends or family outside the household. Finally, indicators for the individual's relationship within the household were included, reflecting 11 categories of relationships such as single parents with children, elderly couples, and dependent students.

At the household level, we included the number of child and adult household members, indicators for dwelling type, categorised as 'Separate house' (omitted), 'Semi-detached, townhouse, or terrace', 'Flat', or 'Other' (*e.g.*, non-private residential home, cabin, boathouse), real household annual disposable income per household member, indicators for each SEIFA IRSAD decile (first decile omitted), and for remoteness area for the household, categorised by the Australian Statistical Geography Standard (ASGS) as "Major Cities of Australia" (omitted), "Inner Regional Australia", "Outer Regional Australia", "Remote Australia", and "Very Remote Australia", with the latter two combined in our analysis due to low prevalence rates in the sample.

6.3 Choice of Estimator

In the hypothetical setting where an extended lockdown was indefinitely imposed at the same time in one or more regions of Australia, *Equation (1)* could be estimated to obtain the causal effect of extended lockdown on mental health through the simple two-way fixed effects (TWFE) difference-in-differences (DD) estimator. In this setting, $\hat{\beta}_1$ would provide the average treatment effect on the treated (ATT). However, heterogeneity in the introduction of extended lockdowns between the states of Australia means that the standard TWFE model may lead to biased estimates for the ATT of lockdown on mental health (Roth *et al.*, 2023). This issue arises as with a staggered intervention, the simple TWFE estimate for ATT represents a weighted average of multiple comparisons between groups (Goodman-Bacon, 2021). Specifically, we are comparing:

1) An early-treated group (Victoria in 2020) versus a never-treated group (Queensland, SA, WA, NT, and Tasmania).

2) A later-treated group (NSW and ACT in 2021) versus a never-treated group (Queensland, SA, WA, NT, and Tasmania).

3) An early-treated group (Victoria in 2020) versus a later-treated group before it is treated (NSW and ACT in 2020).

4) A later-treated group (NSW and ACT in 2021) versus an earlier treated group after they have been treated (Victoria).

This final comparison is what may bias the TWFE estimator when treatment effects vary by time or by treatment cohort (Nasseh and Bowblis, 2022).

Several authors have proposed estimation methods to address this issue with TWFE estimation. Callaway and Sant'Anna (2021) derived an event-study estimator which accounts for staggered treatment entry. The estimator uses outcome regression, inverse probability weighting, and doubly robust methods to produce DD estimates (Nasseh and Bowblis, 2022). Essentially, the method involves the calculation of an ATT at each subsequent time period for cohorts defined by their first period of treatment. The method allows the researcher to either compare treated cohorts to never treated cohorts or to also include not-yet treated cohorts as controls (Roth *et al.*, 2023). With our data, this method would produce a ATTs for residents of Victoria for 2020 compared to 2019 and 2021 compared to 2019, whilst residents of NSW and ACT would receive an estimated ATT for 2021 compared to 2020. The key drawback of the approach for the purpose of this study is that it does not allow for estimating moderated treatment effects by covariates.

de Chaisemartin and d'Haultfoeuille (2020) also proposed a DD event-study estimator. Unlike the Callaway and Sant'Anna (2021) estimator, this can be utilised with non-absorbing treatments. The premise of the estimator is that it calculates treatment effects for 'switchers' who reflect groups of individuals whose treatment status changes over the study period (de Chaisemartin *et al.*, 2023). The estimated treatment effects are robust to heterogeneity across groups and time (Fabre, 2023). With our data, the estimator would produce aggregated ATTs for first-time 'switchers' to extended lockdown (*i.e.*, Victoria in 2020, NSW and ACT in 2021), and for the subsequent period of treatment for Victorians in 2021, as well as an aggregated ATT across all treated units. One drawback of the estimator is that it does not easily allow for the estimation of moderating effects. Specifically, it only allows for moderation with discrete sub-groups in which individuals cannot change between sub-groups. Thus, estimation of moderating effects is largely constrained to easily definable sub-groups such gender.

Finally, Wooldridge (2021) illustrated that there is nothing inherently wrong with TWFE estimation with staggered treatment entry except in the way it has previously been utilised to generate ATT estimates (Nasseh and Bowblis, 2022). As such, the author proposed an 'extended' two-way fixed effects (ETWFE) estimator which utilises interaction terms to account for staggered treatment, producing ATTs by treatment cohort and time. The approach is akin to that of Callaway and Sant'Anna (2021) except it utilises standard regression methods, meaning that one can easily incorporate terms to allow for heterogeneous treatment effects between sub-groups (Nasseh and Bowblis, 2022). As such, we chose to utilise the ETWFE estimator in our baseline analysis.

6.4 Baseline Estimation Methods

The following sub-section provides details on how we applied the ETWFE estimator to our data. We begin by outlining the approach without covariate adjustment. Subsequently, we present a model which allows for covariate adjustments. We then illustrate how we incorporated moderating effects of the Big Five personality traits within the ETWFE framework.

6.4.1 ETWFE without Covariate Adjustment

We applied the ETWFE approach without covariate adjustment as follows. We firstly defined:

$i = 1, \dots, N$ individuals.

$t = 1, \dots, 17$ time periods (for waves 5 to 21).

$c = 1, \dots, 13$ GCCSAs.

$r = 20, 21$ treated cohorts (*i.e.*, treated in waves 20 and 21).

The first imposition of extended lockdown was defined as occurring at $1 < q \leq T$. We then defined the following variables as per Wooldridge (2021):

$\{fs_t : t = 2, \dots, T\}$ time (wave) fixed-effects indicators with $fs_t = 1$ if $s = t, fs_t = 0$ if $s \neq t$.

$\boldsymbol{d} = d_{cr}, \dots, d_{cT}, d_{c\infty}$ cohort indicators, which are exhaustive and mutually exclusive, with $d_g = 1$ if the unit first entered extended lockdown in period g, and $d_\infty = 1$ if the unit was never treated by extended lockdown. Thus, with our data we defined: $d_{c2020} = 1$ if an individual was first under extended lockdown in wave 20 (Victoria) and 0 otherwise; $d_{c2021} = 1$ if an individual was first under extended lockdown in wave 21 (NSW and ACT) and 0 otherwise; and $d_{c\infty} = 1$ if an individual resided in a GCCSA which never implemented extended lockdown (Queensland, SA, WA, NT, Tasmania), and 0 otherwise (this was omitted as the reference category).

$w_{rt} = d_{cr} * fs_t$ are time-varying treatment indicators for r cohorts. Thus, with our data we defined: $w2020_{20} = 1$ if an individual was first under extended lockdown in 2020 and observed in wave 20 (Victoria), and 0 otherwise; $w2020_{21} = 1$ if an individual was first under extended lockdown in 2020 and observed under extended lockdown in wave 21 (Victoria), and 0 otherwise; and $w2021_{21} = 1$ if an individual was first under extended lockdown in 2021 and observed in wave 21 (NSW and ACT), and 0 otherwise.

Without covariate adjustment, the ETWFE model is:

Equation (2)

$$E(MHI_{it}|\boldsymbol{d}) = \alpha + \sum_{r=20,21} \lambda_r \, d_{cr} + \sum_{s=6,\ldots,21} \theta_s \, fs_t + \sum_{r=20,21} \sum_{s=r}^{21} \tau_{rs} w_{rt}$$

Where the coefficient τ_{rs} gives the ATTs for cohort r at time s. For our data, this would produce three ATTs of extended lockdown on mental health, one for residents of Victoria in 2020, one for residents of Victoria in 2021, and one for residents of NSW and ACT in 2021.

Before proceeding, it was necessary to test the parallel trends assumption. Wooldridge (2021) outlined this can be conducted by including cohort-specific linear time trends, $d_{cr} * t$, noting that inclusion of the polynomial $t = 1, \ldots, T$ is preferable to including a full set of cohort-wave indicators ($d_{cr} * fs_t$) as this allows for a constant difference between the treated and control units. Thus, we estimated the following equation:

Equation (3)

$$E(MHI_{it}|\boldsymbol{d}) = \alpha + \sum_{r=20,21} \lambda_r \, d_{cr} + \sum_{s=6,\ldots,21} \theta_s \, fs_t + \sum_{r=20,21} \sum_{s=r}^{21} \tau_{rs} w_{rt} + \sum_{r=20,21} \omega_r (d_{cr} * t)$$

The model was estimated using fixed effects regression absorbing individual- and GCCSA-level fixed effects using the *reghdfe* command (Correia, 2014) in Stata 17 (StataCorp, 2021). Robust standard errors were clustered at the GCCSA level. Note that the cohort fixed effects (d_{cr}) were omitted as they are time-invariant. The command also automatically dropped singleton observations, as their inclusion can affect the size of the estimated standard errors leading to incorrect inference (Correia, 2015). The parallel trends assumption was tested by $H_0: \omega_{20} = \omega_{21} = 0$ using a cluster-robust Wald statistic (Wooldridge, 2021). Rejection of the null implies a violation of the parallel trends assumption.

Column 1 of Table C1 in Appendix 3C provides the results from this test. The estimated coefficients on the cohort-time trends were positive and statistically significant, whilst the Wald F statistic indicated rejection of the null hypothesis. However, Wooldridge (2021) shows that including the final term in *Equation 3* in all estimation models can act as a correction for this violation. Furthermore, when one conditions on covariates, the parallel trends assumption can be relaxed further by allowing for heterogeneity across trends to depend on observed covariates. We detail this procedure in the following sub-section.

6.4.2 ETWFE with Covariate Adjustment

Wooldridge (2021) showed we can extend *Equation (3)* to condition on vectors of individual level time-varying ($\boldsymbol{X_{it}}$) and time-invariant ($\boldsymbol{X_i}$) covariates. The time-varying covariates must be

exogenous in the sense that current values of y_{it} do not affect future values of $\boldsymbol{X_{it}}$, and further that $\boldsymbol{X_{it}}$ does not react to treatment. The model can also be augmented by the term $\sum_{r=20,21}(d_{cr} * fs_t * \boldsymbol{X_{it}})\ \boldsymbol{\gamma_r}$ to allow for heterogeneity across trends to depend on observed covariates, as shown by *Equation (4)*.

Equation (4)

$$
\begin{aligned}
&E(y_{it}|\boldsymbol{d}, \boldsymbol{X_i}, \boldsymbol{X_{it}}) \\
&\quad = \alpha + \boldsymbol{X_i}\boldsymbol{\kappa_i} + \boldsymbol{X_{it}}\boldsymbol{\kappa_{it}} + \sum_{r=20,21} \lambda_r\, d_{cr} + \sum_{r=20,21} (d_{cr} * \boldsymbol{X_i})\boldsymbol{\varsigma_r} \\
&\quad + \sum_{g=q}^{T} (d_{Cr} * \boldsymbol{X_{it}})\boldsymbol{\eta_g} \sum_{s=6,\ldots,21} \theta_s\, fs_t + \sum_{s=2}^{21} (fs_t * \boldsymbol{X_i})\boldsymbol{\pi_t} + \sum_{s=2}^{21} (fs_t * \boldsymbol{X_{it}})\boldsymbol{\phi_t} \\
&\quad + \sum_{r=20,21} \sum_{s=r}^{21} \tau_{rs} w_{rt} + \sum_{r=20,21} \omega_r (d_{cr} * t) + \sum_{r=20,21} (d_{cr} * fs_t * \boldsymbol{X_{it}})\boldsymbol{\gamma_r}
\end{aligned}
$$

For our analysis, we considered the following covariates as satisfying the condition of strict exogeneity. Firstly, the Big Five personality traits, defined by the vector $\boldsymbol{PN_{it}}$. Second, the time-varying variables for age group, number of adult and child household members, decile of the SEIFA index of relative social advantage and disadvantage, education, family relationship, dwelling type, region type, and marital status were defined by $\boldsymbol{X_{it}}$. We also included the sole time-invariant individual-level covariate of male gender, *i.e.*, $\boldsymbol{X_i} \equiv Male_i$.

To account for covariates which would likely fail the requirement of strict exogeneity, we implemented the entropy balancing approach proposed by Hainmueller (2012). This is a data pre-processing method which creates balanced samples between a treatment and control group. In our case, we defined the treatment group as individuals who were observed under extended lockdown (*i.e.*, residents of Victoria, NSW, and ACT) whilst the control group consists of those who were 'never treated' (*i.e.,* the rest of Australia).

The first step imposed a set of balance constraints on the first and second moments of the selected covariates. In our case, this included gender, personality, and all exogenous covariates contained in $\boldsymbol{X_{it}}$, alongside the first lag of the potentially endogenous covariates including employment status, self-rated health, long-term health conditions, smoking status, weekly alcohol consumption, social support index, frequency of social contact, self-rated financial status, negative life events, and real household disposable income per capita. We utilised the first lag of these potentially endogenous covariates to avoid post-treatment bias. Entropy balancing then applied unit weights such that the reweighted control group almost exactly matched the treatment group on the first and sample moments of these covariates. Intuitively, this effectively ensured that our selected observable

characteristics of the treatment and control group were as similar as possible, mimicking the conditions of a randomised controlled experiment (Neuenkirch and Neumeier, 2016). Table D1 in Appendix 3D illustrates the efficacy of the approach, showing that the first and second moments of our covariates were near-identical following entropy balancing. The second step utilised the estimated unit weights in the ETWFE model.

Previous studies utilising the EWTFE approach have used the alternative matching approach of propensity score matching (PSM) (Nasseh and Bowblis, 2022). However, the advantage of entropy balancing is that it allows for the retention of the full sample for the analysis, whereas PSM can discard significant proportions of the full sample. Additionally, if only a sub-set of control units are utilised in PSM, this can lead to insufficient balance of the pre-treatment characteristics between the treatment and control group, potentially leading to biased estimates of the treatment effect (Neuenkirch and Neumeier, 2016).

Hence, we estimated *Equation (5)* using linear fixed effects regression on the entropy balanced sample.

Equation (5)

$$
\begin{aligned}
&E(MHI_{it}|\boldsymbol{d}, \boldsymbol{PN_{it}}, \boldsymbol{Male_i}, \boldsymbol{X_{it}}) \\
&= \alpha + \boldsymbol{PN_{it}}\boldsymbol{\beta_{it}} + \kappa_i Male_i + \boldsymbol{X_{it}}\boldsymbol{\kappa_{it}} + \sum_{r=20,21} \lambda_r \, d_{cr} + \sum_{g=q}^{T} (d_{Cr} * \boldsymbol{PN_{it}})\boldsymbol{\gamma_g} \\
&+ \sum_{r=20,21} \varsigma_r (d_{cr} * Male_i) + \sum_{g=q}^{T} (d_{Cr} * \boldsymbol{X_{it}})\boldsymbol{\eta_g} + \sum_{s=6,\ldots,21} \theta_s \, fs_t \\
&+ \sum_{s=2}^{21} (fs_t * \boldsymbol{PN_{it}})\boldsymbol{\varphi_t} + \sum_{s=2}^{21} \pi_t (fs_t * Male_i) + \sum_{s=2}^{21} (fs_t * \boldsymbol{X_{it}})\boldsymbol{\phi_t} \\
&+ \sum_{r=20,21} \sum_{s=r}^{21} \tau_{rs} w_{rt} + \sum_{r=20,21} \omega_r (d_{cr} * t) + \sum_{r=20,21} (d_{cr} * t * \boldsymbol{PN_{it}})\boldsymbol{\epsilon_r} \\
&+ \sum_{r=20,21} (d_{cr} * t * \boldsymbol{X_{it}})\boldsymbol{\gamma_r}
\end{aligned}
$$

Note that as we utilised the lag of the potentially endogenous variables to avoid post-treatment bias, our estimation sample was slightly smaller than that used in the ETWFE model without covariate adjustment, since some individuals had missing data on their previous observation. Also note that the first lag of the endogenous variables in wave 5 are drawn from observations in wave 4, which was not utilised in the analysis as personality was not measured until wave 5.

We then re-tested $H_0: \omega_{20} = \omega_{21} = 0$, with the results provided in Column 2 of Table C1 in Appendix 3C. This indicates the parallel trends assumption held once we allowed for heterogenous trends to depend on our observed covariates.

Before proceeding, we tested the second key assumption of the ETWFE model for no anticipation by including the lead of the time-varying extended lockdown indicator defined as:

$$W_{it} = \begin{cases} 1 \; if \; under \; extended \; lockdown \\ 0 \; otherwise \end{cases}$$

and estimating the following equation using fixed effects regression with entropy balancing, absorption of individual- and GCCSA-level fixed effects, and cluster-robust standard errors clustered at the GCCSA level (Wooldridge, 2021):

Equation (6)

$$E(MHI_{it}|\boldsymbol{d}, \boldsymbol{PN_{it}}, \boldsymbol{Male_i}, \boldsymbol{X_{it}}) = \alpha + \sum_{r=20,21} \lambda_r \, d_{cr} + \sum_{s=6,\ldots,21} \theta_s \, fs_t + + \sum_{s=2}^{21} (fs_t * \boldsymbol{PN_{it}}) \boldsymbol{\varphi_t} + \sum_{s=2}^{21} \pi_t (fs_t * Male_i) + \sum_{s=2}^{21} (fs_t * \boldsymbol{X_{it}}) \boldsymbol{\phi_t} + \zeta_{it} W_{it+1}$$

We then tested $H_0: \zeta_{it} = 0$ using the cluster-robust *t*-test statistic. We found we could not reject the null hypothesis, and thus there was evidence for the no anticipation assumption (see Table C2 in Appendix 3C for the results).

As such, *Equation (5)* above represents the baseline specification used for testing our first hypothesis. As per *H1,* we expected the estimated ATTs contained in τ_{rs} to be negative for the time-varying cohort treatment indicators w_{rt} representing individuals residing in Victoria under extended lockdown in 2020 and again in 2021, and individuals residing in NSW and ACT under extended lockdown in 2021.

Wooldridge (2021) shows that these estimates can be aggregated to produce an overall aggregated treatment effect, $\hat{\tau}$, or a cohort-specific aggregated treatment effect, $\widehat{\tau_r}$, as follows:

Equation (7)

$$\hat{\tau} = \frac{1}{(Total \; Estimated \; ATTs)} \sum_{r=20,21} \sum_{s=r}^{21} \widehat{\tau_{rs}}$$

Equation (8)

$$\widehat{\tau_r} = \frac{1}{(21 - r + 1)} \sum_{s=r}^{21} \widehat{\tau_{rs}}$$

Thus, *Equation (7)* gave the aggregated effect of the estimated ATTs for the Victorian cohort of extended lockdown in 2020 and 2021 alongside the NSW and ACT cohort of extended lockdown in 2021.

Note that for *Equation (8),* $\widehat{\tau_r} = \widehat{\tau_{rs}}$ for the 2021 NSW and ACT cohort as only one ATT is estimated for them, however for the Victoria cohort this produces an aggregated ATT of the effect of extended lockdown in 2020 and 2021.

6.4.3 ETWFE with Moderating Effects by Personality

To test our second set of hypotheses, we extended *Equation (5)* to further include triple difference-in-differences (DDD) terms for heterogeneous effects by each of the Big 5 personality traits. Wooldridge (2021) shows that to recover these moderating effects, it is necessary to demean the personality traits by cohort/time in the following way:

$$\dot{\boldsymbol{PN}}_{\boldsymbol{itr}} \equiv \boldsymbol{PN_{it}} - N_r^{-1} \sum_{h=1}^{N} d_{hr} \, fs_t \boldsymbol{PN_{ht}}$$

That is, for each individual *i* in cohort *r* at time *t,* we demeaned each personality trait by its mean value across cohort *r* at time *t*. We then augmented *Equation (5)* with the interaction between $\dot{\boldsymbol{PN}}_{\boldsymbol{itr}}$ and each of the time-varying cohort lockdown indicators w_{rt}. The exact specification is given by:

Equation (9)

$$\begin{aligned} E(MHI_{it} | \boldsymbol{d}, \boldsymbol{PN_{it}}, \boldsymbol{Male_i}, \boldsymbol{X_{it}}) \\ = \alpha + \boldsymbol{PN_{it}}\boldsymbol{\beta_{it}} + \kappa_i Male_i + \boldsymbol{X_{it}}\boldsymbol{\kappa_{it}} + \sum_{r=20,21} \lambda_r \, d_{cr} + \sum_{g=q}^{T} (d_{Cr} * \boldsymbol{PN_{it}})\boldsymbol{\gamma_g} \\ + \sum_{r=20,21} \varsigma_r (d_{cr} * Male_i) + \sum_{g=q}^{T} (d_{Cr} * \boldsymbol{X_{it}})\boldsymbol{\eta_g} + \sum_{s=6,\dots,21} \theta_s \, fs_t \\ + \sum_{s=2}^{21} (fs_t * \boldsymbol{PN_{it}})\boldsymbol{\varphi_t} + \sum_{s=2}^{21} \pi_t (fs_t * Male_i) + \sum_{s=2}^{21} (fs_t * \boldsymbol{X_{it}})\boldsymbol{\phi_t} \\ + \sum_{r=20,21} \sum_{s=r}^{21} \tau_{rs} w_{rt} + \sum_{r=20,21} \sum_{s=r}^{21} (w_{rt} * \dot{\boldsymbol{PN}}_{\boldsymbol{itcr}})\boldsymbol{\rho_{rs}} + \sum_{r=20,21} \omega_r (d_{cr} * t) \\ + \sum_{r=20,21} (d_{cr} * t * \boldsymbol{PN_{it}})\boldsymbol{\epsilon_r} + \sum_{r=20,21} (d_{cr} * t * \boldsymbol{X_{it}})\boldsymbol{\gamma_r} \end{aligned}$$

This was estimated using fixed effects regression controlling for individual- and GCCSA-level fixed effects using entropy weights. The terms contained in the vector $\boldsymbol{\rho_{rs}}$ give the moderating effect of each personality trait for the treatment cohort under each period of extended lockdown. Thus, per *H2a*, we expected the terms pertaining to the moderating effects of extroversion and openness contained in $\boldsymbol{\rho_{rs}}$ to be negative. Per *H2b*, we expected these terms to be positive when pertaining to emotional stability, agreeableness, and conscientiousness.

6.5 Robustness Checks

We conducted the following five robustness checks of our estimation method, outcome variable, lockdown measure, and identification strategy.

6.5.1 Robustness Check 1: Alternative DID Estimators

We firstly checked the robustness of the results obtained using the EWTFE by employing two alternative estimation methods, the Callaway and Sant'Anna (2021) staggered difference-in-difference estimator (herein: CS) for the general effect of extended lockdowns on mental health and the de Chaisemartin and d'Haultfoeuille (2020) estimator (herein: CH).

The CS approach is similar to the EWTFE approach, and thereby allowed for a direct robustness check of our baseline results testing *H1*. However, the estimator cannot currently be utilised to directly test for moderating effects. As such, we instead qualitatively checked the robustness of the ETWFE results for *H2* by stratifying the sample into low (below median) and high (equal to or above median) sub-samples for each of the five traits. We implemented the approach using the *csdid* user-written Stata estimation command (Rios-Avila *et al.*, 2021). Note that this method only provides descriptive differences in the estimated treatment effects between the stratified personality samples as tests of differences between the two sub-samples cannot be conducted post-estimation with this Stata package.

The CH approach differs from the EWTFE and CS methodology by instead estimating dynamic ATTs which reflect treatment intensity. As such, it produced ATTs for the average effect of first treatment (*i.e.*, the aggregated effect for residents of Victoria experiencing their first extended lockdown in 2020 and for residents of NSW and ACT experiencing their first extended lockdown in 2021) and for each subsequent post-treatment period (*i.e.*, for residents of Victoria experiencing a second extended lockdown in 2021). It also produced an overall average ATT for experience of extended lockdowns. As the estimator can only use the same number of pre- and post-treatment periods, only four waves of the data were utilised to obtain the ATT estimates. It is possible to obtain moderating effects using the CH estimator by calculating the within-GCCSA difference in mean MHI between two sub-groups for each time period, and then utilising this as the outcome

variable. In theory, we could apply this to the low and high sub-groups for personality as defined above, however this is only valid if individuals do not move between groups, which was not the case in our data[13]. Therefore, we re-estimated the CH models stratifying by sub-group as done for the CS robustness check. We implemented the CH estimator via the user-written *did_multiplegt_dyn* command in Stata 17 (de Chaisemartin *et al.*, 2023).

6.5.2 Robustness Check 2: OxCGRT Stringency Index and State Deaths and Cases

Next, we explored the relationship between mental health and policy stringency captured by the OxCGRT stringency index. As ETWFE is designed for use with binary treatment variables, we instead estimated standard linear fixed effects models including the Stringency Index and its interaction with each of the Big 5 personality traits alongside our selected covariates. This reduced causal inference but provided additional information on how personality may influence the relationship between increasing levels of stringency and mental health. We estimated the model with and without the cumulative state-level COVID-19 deaths and cases. Note that the requirements of the ETWFE method also precluded the use of the death and cases variables in our baseline analysis as they almost certainly would fail the conditions for strict exogeneity as implementation of lockdown conditions reduces community transmission and deaths.

6.5.3 Robustness Check 3: Tests of Identification Strategy

In our baseline identification strategy, we defined the treatment groups as all individuals residing in states which implemented extended lockdowns in 2020 and 2021. A small proportion of individuals were surveyed in waves 20 and 21 prior to extended lockdowns being implemented or after they were lifted. We therefore tested the robustness of our baseline results to exclusion of these individuals in three ways:

1) Removing just individuals interviewed 'pre-lockdown' in waves 20 and 21 from the sample.

2) Removing individuals interviewed 'pre-lockdown' and those interviewed 4 weeks after the end of extended lockdown from the sample.

3) Removing all individuals who were interviewed outside the dates of extended lockdowns in waves 20 and 21 from the sample.

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[13] In our sample, 6.63% of individuals move between the low and high extroversion groups, 8.19% move between the low and high emotional stability groups, 7.91% move between the low and high agreeableness groups, 7.6% move between the low and high conscientiousness groups, and 7.37% move between the low and high openness groups.

6.5.4 Robustness Check 4: Greater Capital Cities

As a further check, we re-estimated our baseline models using only residents of the Greater State Capital Cities where possible. Specifically, we only utilised observations on individuals residing in Greater Melbourne (Victoria), Greater Sydney (NSW), ACT (remains the same), Greater Brisbane (Queensland), Greater Adelaide (SA) and Perth (WA), whilst for NT and Tasmania the same individuals were utilised as lower disaggregation was not available. This was not considered problematic as such individuals were never-treated observations. The purpose of this was three-fold. Firstly, residents of the Greater Capital Cities provided a higher proportion of completed SCQs during the extended lockdown dates than those in the Rest of State regions. Second, the stringency of the extended lockdowns imposed in Victoria was higher for Greater Melbourne than for the rest of the state, as, on top of stay-at-home orders, a curfew was imposed. Lastly, we could compare our results for the estimated effect of extended lockdown to those obtained by Li *et al.* (2023) who only utilised observations on individuals residing the Greater State Capitals.

6.5.6 Robustness Check 5: Two-Way Fixed Effects Estimation

Finally, we estimated *Equation (1)* using the simple TWFE estimator whereby the specification only included a single time-varying indicator for extended lockdown, equal to 1 for all residents of Victoria in 2020 and 2021, and for all residents of NSW and ACT in 2021, and 0 otherwise. This also served as a robustness check to examine whether the covariates we included in our baseline specification exhibited the expected relationships with mental health.

7. Results

7.1 The Effect of Extended Lockdown on Mental Health

The results from estimating the ETWFE models specified by *Equation (3)* (no covariate adjustment) and *Equation (4)* (with covariate adjustment) are presented in Table 7.1 in columns 1 and 2 respectively. Both models included cohort-time indicators (*'D2020 x T', 'D2021 x T'*) to correct for the failure of the parallel trends assumption by allowing for heterogenous trends, whilst the covariate adjusted model also included triple interaction terms between the covariates (including personality) and the cohort-time indicators to allow for the heterogeneous trends to be conditional on our covariates. Both models were estimated using fixed effects regression controlling for time, GGCSA, and individual fixed effects. The model with covariate adjustment also utilised entropy balancing weights to adjust the first and second moments of observed characteristics between the treated and never-treated individuals in the sample. This included personality and the strictly exogeneous covariates utilised in the model, as well as the pre-treatment values (first lag) of potentially endogenous covariates. Note the sample size fell from 187,074 to 164,841 observations due to missing observations on the first lag of the possibly endogenous variables.[14]

Table 7.1 first presents the three cohort-time estimated ATTs for the effect of extended lockdown on MHI-5 score. Comparing columns 1 and 2 indicates that adjustment for covariates did not qualitatively change the results. In support of *H1,* all estimated ATTs were negative and statistically significant. The table then presents the aggregated estimated ATTs. The first of these represents the average effect of extended lockdown on MHI-score for residents of Victoria across 2020 and 2021. The second represents the average effect of extended lockdown across cohorts and time. The final aggregated ATT represents the average effect of extended lockdown in 2021. This was close in magnitude to the estimated effect of extended lockdown in 2020, suggesting that there was little heterogeneity in the effect of extended lockdowns across time. However, aggregating at this level ignores the important finding that there was heterogeneity across cohorts. Namely, the average effect of extended lockdown on Victorian residents across 2020 and 2021 was greater than the effect of extended lockdown for residents of NSW and ACT who experienced extended

[14] We re-ran the model without adjustment for covariates on this smaller sample to check the extent to which the difference in the ATTs displayed in columns 1 and 2 of Table 7.1 were due to a change in sample. The results from this are available in Table E13 in Appendix 3E. This estimated only marginally smaller ATTs than in the original sample utilised for column 1, indicating most of the reduction in ATT size in column 2 was a result of the covariate adjustment.

lockdown only in 2021. We now interpret the magnitude of these estimated effects from the covariate adjusted model in column 2.

Firstly, the results indicate the effect of extended lockdown in 2020 for was to reduce MHI-5 score by 1.485 points for Victorian residents. This is equivalent to a 2.09% reduction compared to the pre-pandemic (*i.e.*, waves 5 to 19) sample mean. Victorians under a second extended lockdown experienced a reduction in MHI-5 score of 2.140-points relative to the pre-pandemic level, equivalent to a 3.89% reduction relative to the pre-pandemic sample mean. The estimated aggregated ATT for Victorians across both years indicated the average effect of extended lockdown was to reduce MHI-5 score by 1.812 points. For residents of NSW and ACT, who first experienced extended lockdown in 2021, the ATT indicates MHI-5 scores fell by 0.815 points following the imposition of extended lockdown. This is equivalent to a 1.10% reduction relative to the pre-pandemic sample mean. Across all cohorts, the estimated aggregated ATT indicates that the imposition of an extended lockdown reduced on average MHI-5 score by 1.480 points. Finally, the estimated aggregated effect of an extended lockdown on MHI-5 score in 2021 was to reduce mental health by 1.478 points.

Taken together, these results are consistent with the existing literature which showed a negative association between lockdowns and mental health in Australia (Fisher *et al.*, 2021; Leach *et al.*, 2023; Butterworth *et al.*, 2022; Hale *et al.*, 2023; Li *et al.*, 2023). Furthermore, consistent with Li *et al.* (2023) we find that extended lockdowns in both 2020 and 2021 negatively impacted mental health, extending the authors findings to residents of the entire states and not just those residing in the Greater Capital Cities. We also find that consistent with Li *et al.* (2023), the time aggregated effects of extended lockdown in 2020 and 2021 were almost identical.

However, the results provide new evidence of a heterogeneous cohort effect which was not modelled by Li *et al.* (2023). Specifically, the findings indicate that the imposition the extended lockdown in Victoria in 2020 had the largest effect on mental health whilst the imposition of the second extended lockdown further reduced mental health, but the effect was approximately halved[15]. This effect of the 2021 lockdown in Victoria was approximately 0.160 points smaller than the effect of the imposition of extended lockdown in NSW and ACT in 2021. Together, this firstly suggests that the imposition of a first extended lockdown had a greater negative effect on mental health than the imposition of a subsequent extended lockdown. Second, it suggests that the

[15] In the covariate-adjusted model the difference between the 2020 and 2021 extended lockdown ATTs (in absolute terms) is 0.655, indicating this was the effect of the second imposition on the mental health of Victorians.

imposition of the first extended lockdown in Victoria had a significantly greater effect than the imposition of the first extended lockdown in NSW and ACT. We now speculate on the reasons for this finding.

It is plausible that Victorian's mental health deteriorated more during the first extended lockdown as they were the only state under such conditions, and thus the comparative freedom of the rest of the country may have induced a greater psychological response. In 2021, the knowledge of a shared burden of lockdown with residents of NSW and ACT may have eased this impact somewhat. Furthermore, Victorians may have learned from their first experience of extended lockdown and thus may have possessed better strategies to protect their mental health the second time. It may also be the case that for residents of NSW and ACT, their mental health was less fragile prior to entering lockdown in 2021 as they had enjoyed more than a year of relative freedom. This could further explain why their mental health in 2021 deteriorated at a lesser rate relative to residents of Victoria in 2020.

7.2 The Moderating Effect of Personality

We next present and discuss the results from the estimation of the ETWFE with moderating effects by the Big Five personality traits, represented by *Equation (5)*. Table 7.2 presents the cohort-time specific estimated ATTs, with the aggregated ATTs for the Victorian cohort and across all cohorts and time presented in Table 7.3. The results in column 1 of both tables were not adjusted for additional covariates beyond the Big Five personality traits and did not utilise entropy weights. The results in column 2 instead adjusted for covariates and used entropy weights. The results were qualitatively similar across both specifications. As such, we discuss the results presented in column 2 in detail. The reader is reminded that the personality traits were normalised on a scale of 0 to 1, and thus the estimated ATTs represent the differential effect of lockdown between the extremes of each personality trait.

Column 2 of Table 7.2 firstly indicates the estimated ATTs for the effects of extended lockdown were similar to those obtained in the model without moderating effects. Next, in partial support of *H2a*, we find that extroversion negatively moderated the effect of extended lockdown on mental health. However, this moderating effect was only statistically significant for the Victoria cohort. Specifically, extreme extroverts experienced a further 4.727-point reduction in MHI-5 score relative to extreme introverts as a result of the 2020 extended lockdown. Combined with the effect of the lockdown itself, this meant extreme extroverts experienced a reduction in MHI-5 score of 6.229 points, equivalent to an 8.39% reduction compared to the pre-pandemic sample mean. This moderating effect was reduced to -2.431 points in the second extended lockdown in 2021 for

residents of Victoria. This indicates that the moderating effect of extroversion waned between the first and second extended lockdowns in Victoria, although extroversion remained an important moderating factor. This is consistent with the proposal of Proto and Zhang (2021), who suggested that extroverts may find ways to adapt to satisfy their desire for social interactions over time.

Conversely, we find that extroversion did not significantly moderate the effect of extended lockdown on mental health in the NSW and ACT cohort. It should be noted that the point estimate for the extroversion interaction term for NSW and ACT was still negative, albeit smaller than that for Victoria in 2021 (-1.697 versus -2.431). One partial explanation for this may be that whilst all residents of Greater Melbourne (where most of the population of Victoria reside) were subjected to curfew throughout the 2021 extended lockdown, only residents in specific LGAs of concern in NSW and no residents of ACT were subjected to such curfews. As such, extroverts within NSW and ACT may have had more opportunity to interact with the outside world (for the permitted reasons such as exercise or essential shopping) than those in Greater Melbourne.

Column 2 of Table 7.3 indicates that when we aggregated across all cohorts and time, extreme extroverts experienced a 2.952-point decline in mental health relative to extreme introverts under extended lockdown, with this effect statistically significant at the 1% level. This is consistent with all four studies which explicitly explored the moderating effect of extroversion during the pandemic (Wijngaards *et al.*, 2020; Zacher and Rudolph, 2021; Staneva *et al.*, 2022; Proto and Zhang, 2021). Overall, this suggests that the negative mental health effects from the inhibition of social interactions imposed by extended lockdowns outweighed any protective effects from extroverts' tendency to adapt better to adverse events and retain their positive affect for longer following such events (Proto and Zhang, 2021; Li *et al.*, 2021; Shokrkon and Nicoladis, 2022; Staneva *et al.*, 2022). This is perhaps not surprising given the prolonged nature of the lockdowns experienced by residents of Victoria, NSW, and ACT, meaning maintenance of positive affect throughout lockdown was unlikely.

In *H2a*, we also postulated that openness would negatively moderate the effect of extended lockdown. However, for residents of Victoria, we find evidence of a converse effect during the 2020 extended lockdown, whilst the mental health effects of extended lockdowns imposed in 2021 in Victoria, NSW, and ACT were not moderated by openness. For Victoria in 2020, the estimated ATT in column 2 of Table 7.3 implies that individuals with extremely high openness experienced a protective effect against the mental health impact of extended lockdown equivalent to a 2.441-point increase in MHI-score. This is larger than the DD estimated effect of the lockdown itself, suggesting lockdown may have benefitted the mental health of extremely open individuals.

This result is largely converse to our expectations that more open individuals would be more susceptible to poorer mental health as their preference for exploration would be inhibited (Proto and Zhang, 2021). However, we postulated that there may be competing mechanisms for openness, which captures broadest range dimensions of all the Big Five personality traits (McCrae, 2004). This result therefore suggests that under the 2020 extended lockdown in Victoria, more open individuals may indeed have fared better from newfound time to act on their creative and intellectual nature, and may have seen the lockdown as an opportunity for personal growth. Indeed, one study conducted during the early pandemic also found a protective moderating role of openness, with the authors suggesting that more open individuals may have actually been more receptive to changes in lifestyle, treating them as novel experiences (Zhang *et al.*, 2021b). However, by 2021 the novelty of this may have dissipated for residents of Victoria, as indicated by the lower and non-statistically significant estimated moderating effect. Equally, residents of NSW and ACT in 2021 had already experienced more than one year of the pandemic and the various other non-lockdown restrictions it entailed, and thus may have been less likely to appraise the imposition of an extended lockdown as a novel experience and more as a hinderance to their inherent preferences for exploration.

Next, we find partial support for *H2b*, in which we postulated that emotional stability, agreeableness, and conscientiousness would have a positive moderating effect on mental health impact of extended lockdown. As per expectations, higher emotional stability had a protective effect against the mental health impact of extended lockdowns, but this was only statistically significant for the Victoria cohort. Column 2 of Table 7.3 indicates this protective effect for the 2020 lockdown was estimated to be equivalent to a 5.071-point increase in MHI-score for highly emotionally stable individuals relatively to highly neurotic individuals. Combined with the ATT for the 2020 lockdown, this suggests that highly emotionally stable individuals may have exhibited improved mental health during the lockdown, whilst highly neurotic individuals suffered significant declines in their mental health. Indeed, for a highly neurotic Victorian resident, the imposition of the 2020 extended lockdown reduced MHI-5 score by 8.86% relative to the pre-treatment sample mean. The protective effect of emotional stability continued for Victorians under their second extended lockdown in 2021, albeit at a reduced level equivalent to 2.975-points. For residents of NSW and ACT, a positive ATT was obtained for the moderating effect of emotional stability, however this was not statistically significant.

One explanation for these findings is that given the tendencies of neurotic individuals to be self-pitying (McCrae and John, 1992), more neurotic individuals in Victoria in 2020 may have believed that being placed under extended lockdown whilst all other states were living with relative freedom

was particularly unfair, and therefore may have considered this situation as the 'world being against them'. In comparison, in 2021 more neurotic residents of NSW and ACT may have been somewhat comforted by the knowledge that other states were also under extended lockdowns. This may, however, have provided less solace for more neurotic individuals residing in Victoria in 2021, as they had cumulatively spent a significantly longer time under extended lockdown than those of NSW and ACT, and indeed the rest of the world (Li *et al.*, 2023).

Overall, when considering the aggregated ATT across time and cohorts presented in Table 7.3, emotional stability was found to protect the mental health of the most emotionally stable under extended lockdown by 2.968 points relative to the most neurotic, with this effect significant at the 1% level. Comparing to the existing literature, this is congruent with findings from Staneva *et al.* (2021) (albeit the authors only showed this by simple stratification of samples by low and high emotional stability), but conflicts the non-significant results obtained by Zacher and Rudolph (2021) and Proto and Zhang (2021). However, neither Zacher and Rudolph (2021) or Proto and Zhang (2021) employed DD estimation in their studies. This suggests overall, the dominant moderating mechanism for emotional stability was the protective influence of resilience and effective coping in response to stressors, with neurotic individuals showing little evidence of any hedonistic adaption from past adverse experiences.

Converse to expectations, agreeableness did not play a particularly significant moderating role in the effect of lockdowns on mental health. For residents of Victoria, a negative moderating effect was estimated during the 2020 lockdown, although this was only borderline statistically significant at the 10% level. For extended lockdowns in 2021, positive but non-statistically significant estimates were obtained for both cohorts. Indeed, the overall aggregated ATT across cohorts and time for agreeableness shown in Table 7.3 was not statistically significant. It is likely that our result may reflect the competing mechanisms hypothesised (*i.e.*, a pro-social attitude versus altruism) cancelling out. This is consistent with the findings of Zacher and Rudolph (2021), although contradicts those of Proto and Zhang (2021) who generally found a negative moderating relationship between agreeableness and mental health deterioration in the UKHLS. However, Proto and Zhang (2021) did not explicitly estimate how personality traits interacted with lockdown measures, but rather just their changing relationship with mental health over the course of the pandemic.

We lastly find that conscientiousness did not play a significant moderating role for either of the cohorts at any time. This is consistent with the findings from most studies in the literature using panel data (Proto and Zhang, 2021; Zacher and Rudolph, 2021). This suggests that in our sample,

the possibility of protective effects for more conscientious individuals from attributes such as motivational stability and persistence are being counteracted by negative mental health effects due to restrictions to their preferences for long-term planning. We may expect this to be the case given the long durations of extended lockdowns in Australia.

Overall, Table 7.3 indicates that across cohorts and time, only extroversion and emotional stability were significant moderators of the effect of lockdown on mental health, with emotional stability appearing to be the most significant moderator. Although this result is inconsistent with some previous studies on the moderating effect of emotional stability during the pandemic (Proto and Zhang, 2021; Zacher and Rudolph, 2021), it fits with the wider literature which consistently found emotional stability to be the most important moderating trait in response to adverse events (Malouff *et al.*, 2005; Kotov *et al.*, 2010; Hakulinen *et al.*, 2015; Strickhouser *et al.*, 2017; Lyon *et al.*, 2021; Batty *et al.*, 2018; McCann, 2010; Lamers *et al.*, 2012; DeNeve and Cooper, 1998; McCann, 2011). Indeed, this finding is not surprising considering that by definition, emotional stability encapsulates an individual's sensitivity to environmental stressors (Widiger and Oltmanns, 2017).

7.3 Robustness Checks

7.3.1 Alternative DID Estimators

7.3.1.1 Callaway and Sant'Anna Estimator

The first robustness check utilised two alternative DID estimators to estimate the effect of extended lockdown on mental health. The first was proposed by Callaway and Sant'Anna (2021), which we denote as the CS estimator. The CS estimator employs an event-study type design to obtain ATTs for cohorts defined by when they were first treated (as in ETWFE). The CS estimator provides ATTs extended lockdown on Victorian residents in 2020 versus 2019 and 2021 versus 2019, and for residents of NSW and ACT in 2021 versus 2020. We utilise both never-treated and not-yet treated observations as the control groups. The model was firstly estimated with just personality as a control variable, and subsequently with all covariates. By design, only base period (the last not treated period) values were utilised for the covariates (including personality). As the method does not allow for moderating effects to be estimated, we subsequently stratified the sample into 'low' (below median) and 'high' (equal to or above median) sub-samples for each personality trait to explore differences in the size of the estimated ATTs. However, these should be interpreted with caution as the output from the *csdid* command in Stata 17 (Rios-Avila *et al.*, 2021) cannot be used for tests of differences between independent samples. The results are presented in Tables 7.4 and 7.5 respectively for the whole sample and stratified sample estimates.

Both columns 1 and 2 of Table 7.4 indicate that, consistent with the ETWFE approach, residents in Victoria exhibited significantly decreased mental health scores in both years under extended lockdown. The estimated ATTs were only slightly different with and without covariate adjustment, and of similar magnitude to those obtained with ETWFE. The estimates in column 2 indicate that MHI-5 score fell by 1.232 points for residents of Victoria under the 2020 extended lockdown relative to 2019. Under the 2021 extended lockdown, MHI-5 score was 2.202 points lower compared to 2019, indicating the effect of the second extended lockdown was to reduce MHI-5 score by a further 0.970 points in Victoria. However, whilst for residents of NSW and ACT a negative ATT was estimated, this was not statistically significant. Note that the output of the CS model indicated a failure of the parallel trends assumption in the NSW and ACT cohort, which may explain this difference. This further illustrates the advantage of using the ETWFE method which augments the models to allow for heterogeneous trends between treatment cohorts to depend on observed covariates.

Turning to Table 7.5, we find the results were consistent with the implications of the point estimates for the moderating relationship of each personality trait obtained in the ETWFE model. For the Victoria cohort, the estimated effect of extended lockdown on mental health was greater for those with higher extroversion, lower emotional stability, higher agreeableness, lower conscientiousness, and higher openness. The differences were most marked for extroversion, emotional stability, and openness, which were the three traits found to significantly moderate the effect of lockdown on mental health for Victorians. Conversely, for the NSW and ACT cohort, no effects on lockdown on mental health were estimated, except for a weakly significant negative effect on low conscientious individuals. This is consistent with the finding from the baseline analysis that personality did not appear to be a significant moderator of the effect of lockdowns on mental health for this cohort.

7.3.1.2 de Chaisemartin and d'Haultfoeuille Estimator

The second alternative estimator utilised was proposed by de Chaisemartin and d'Haultfoeuille (2020), which we denote at the CH estimator. Converse to ETWFE and CS estimation, the CH estimator provides dynamic treatment effects for the first-treated and subsequent treatment periods aggregated together. As such, the estimated ATTs reflect the aggregated effect across cohorts of the first imposition of extended lockdown (2020 for Victoria, 2021 for NSW and ACT), and the subsequent effect of being under extended lockdown in 2021 for Victoria. A further difference is that the estimator only allows for the same number of pre- and post-treatment observations to be utilised when estimating dynamic effects, thus the sample was automatically

restricted to waves 18 to 21. The estimated ATTs were then obtained from samples comparing a control group of untreated individuals with those treated, who are denoted as 'switchers'. As with the CS estimation, we firstly estimated the models on the whole sample (with just personality and with all covariates) and subsequently re-estimated the models on sub-samples stratified by 'low' and 'high' personality trait (controlling for all covariates). The results are provided in Tables 7.6 and 7.7 respectively.

The results in Table 7.6 are consistent with those obtained via ETWFE, indicating that the imposition of extended lockdown significantly reduced mental health. In the model with covariates shown in column 2, the first period of an extended lockdown was estimated to reduce MHI-5 score by 0.986-points, whilst a subsequent period of extended lockdown (*i.e.*, for Victoria only), was associated with a 2.437-point reduction in MHI-5 score relative to pre-pandemic levels. The estimated aggregated effect of the imposition of extended lockdown was to reduce MHI-5 score by 1.407-points. These estimates were similar in magnitude to the equivalent cohort and aggregated ATTs obtained through ETWFE.

Table 7.7 then presents the results from the CHD estimator on the stratified samples. Again, these support the findings from the baseline analysis. The estimated ATTs were consistently larger for individuals with high extroversion and low emotionally stability under both first and second periods of lockdown. This difference was most notable for emotional stability, which was found to be the most significant moderator of the effect of lockdown on mental health using ETWFE. For the remaining traits, the differences in the estimated ATTs were not consistent between first period and second period lockdown effects. This reflects the findings from the ETWFE models whereby agreeableness and openness only significantly moderated the effect of lockdown for Victoria in 2020, and conscientiousness did not significantly moderate the effect of lockdown in any cohort-time period.

Thus, our baseline findings were relatively robust to the alternative estimation methods provided by the CS and CHD estimators, confirming that extended lockdown negatively impacted mental health, and further that this impact varied by individuals' personality traits, particularly emotional stability.

7.3.2 Alternative Policy Stringency Measure

The OxCGRT Stringency Index has previously been utilised to explore the relationship between policy stringency and mental health in a wide variety of contexts (Garcia-Prado *et al.*, 2022; Aknin *et al.*, 2022; Toffolutti *et al.*, 2022), and indeed by one study exploring the moderating effect of extroversion (Wijngaards *et al.*, 2020). The index is measured on a continuous scale from 0 to 100

and was available at the GCCSA level. The daily value of the index was assigned to individuals based on their SCQ date. This enabled us to estimate how policy stringency in general, and not just lockdowns, may relate to mental health, and how the personality traits may moderate this relationship. The models were estimated using linear fixed effects regression, controlling for all covariates and individual, time, and GCCSA fixed effects. Note we do not utilise entropy balancing in the absence of a treatment and control group. For the sake of brevity, we only report the results obtained from the model with moderating effects in Table 7.8. Results from the models without interaction terms between stringency and the Big Five personality traits are available in Table E2 in Appendix 3E.

The first column of Table 7.8 presents the results without the inclusion of cumulative state-level COVID-19 deaths and cases. The estimated coefficient of the stringency index was -0.045 and was statistically significant at the 1% level. This indicates that each unit increase in policy stringency reduces MHI-score by 0.045 points. In wave 20, the mean stringency level in Victoria was 87.22, whilst for all other states it was 57.18. This would approximately translate to a 1.352-point reduction in MHI-score for residents in Victoria relative to other states. This is not dissimilar to the estimated ATT for the effect of extended lockdown in 2020 obtained in the equivalent baseline ETWFE model (-1.502). For 2021, the mean stringency level in states under extended lockdown (Victoria, NSW, and ACT) was 85.76, whilst for all other states it was 54.98. This suggests on average, this difference in stringency would be equivalent to an approximate 1.385-point reduction in MHI-5 score, which again is not dissimilar to the aggregated effect of 2021 lockdown across cohorts.

Some variations emerged in the moderating relationships between personality traits and mental health compared to our baseline analysis. Notably, extroversion did not significantly moderate the relationship between policy stringency and mental health. From the perspective of our study, this finding is not entirely surprising, given that lockdowns are highly stringent policies that impose significant restrictions on freedom of movement. However, under less stringent conditions, individuals often had the freedom to visit leisure facilities, socialise with friends and family, go to work, and dine at restaurants and bars. Therefore, at most levels of policy stringency it was unlikely that extroverts' desire for social interactions was significantly inhibited.

Conversely, we found that emotional stability continued to play a role in positively moderating the effect of policy strictness on mental health in general. This is consistent with the expectation that more emotionally stable individuals generally fared better during the pandemic, which brought about stressors beyond those associated with lockdowns, such as economic uncertainty, potential

illness of oneself or loved ones, or even the loss of friends and family members. Various non-lockdown restrictions as mask mandates, contact tracing, and other forms of social distancing may also have been perceived as stressors by less emotionally stable individuals. Thus, emotionally stable individuals may be better equipped to handle both major events and day-to-day stressors during the pandemic. This aligns with existing literature suggesting that emotional stability can protect mental health in response to both significant negative events and everyday stressors (Ormel *et al.*, 2001; Kendler *et al.*, 2004; Mroczek Almeida, 2004).

Next, we found that agreeableness exhibited a negative moderating relationship with policy strictness and mental health. We found some evidence of such a relationship with extended lockdowns in 2020 in our baseline analysis. As discussed earlier, this result may appear counterintuitive, as higher agreeableness reflects a pro-social attitude and a preference for maintaining social stability. Therefore, one might expect more agreeable individuals to better tolerate restrictions. However, agreeableness is also strongly associated with altruism, meaning that the awareness of others' suffering during the pandemic may negatively impact the mental health of more agreeable individuals (Proto and Zhang, 2021). In this case, it seems that the latter effect may outweigh the former.

Converse to our baseline analysis, we found that conscientiousness positively moderated the relationship between overall policy strictness and mental health. This aligns with the idea that more conscientious individuals may be better equipped to navigate practical constraints resulting from policy restrictions due to their traits such as motivational stability, persistence, and problem-solving skills (Pauly *et al.*, 2021; Proto and Zhang, 2021; Staneva *et al.*, 2022). However, as noted in our discussion of the baseline results, conscientious individuals also tend to prefer making long-term plans (Proto and Zhang, 2021). Thus, it is possible that when considering policy stringency in general, more conscientious individuals may be shielded from poor mental health. However, extended lockdowns may be more likely to limit long-term planning, nullifying this protective effect in our baseline models.

Finally, we found that openness does not significantly moderate the relationship between policy strictness and mental health. This finding is consistent with the results for the 2021 extended lockdowns in our baseline analysis. As previously discussed, openness encompasses a wide range of characteristics, including intellectual curiosity, imagination, artistic tendencies, and acceptance of novel experiences (McCrae, 2004; Proto and Zhang, 2021; Staneva *et al.*, 2022; McCrae and John, 1992; McCrae and Costa, 2003). These traits could plausibly both protect and impair mental

health during the pandemic. Therefore, it appears that when considering policy strictness more broadly, these characteristics may offset each other.

Finally, column 2 of Table 7.8 provides the results with additional controls for state-level COVID-19 deaths and cases. Only the former was significantly associated with mental health, with the estimated coefficient implying each cumulative death within a state reduced MHI-5 score by 0.002 points. The mean difference in death toll between Victoria and the remaining states in wave 20 was approximately 496, roughly translating to a 0.993-point reduction in MHI-5 score. For wave 21, the mean difference in death toll in states between states employing and not employing extended lockdowns was approximately 481, equivalent to a 0.962-point reduction in MHI-5 score. It is notable that the estimated coefficient on policy stringency was smaller with the inclusion of deaths and cases. Policy stringency, deaths, and cases were significantly correlated as tighter restrictions were generally implemented when deaths and cases increased within states. This suggests that when cases and deaths are not accounted for, the stringency index may be capturing some of their effect on mental health due to omitted variable bias. Thus, it should be cautioned that in our baseline analysis, the effect of extended lockdowns on mental health may be reflecting not only the effect of high policy stringency compared to low policy stringency, but also the comparative difference in the severity of the pandemic between states.

7.3.3 Further Robustness Checks

We conducted three further robustness checks. The first tested our identification strategy by removing individuals from the sample who were observed outside of extended lockdown in Victoria, NSW, and ACT. The second restricted the sample to individuals residing in the Greater Capital Cities of Australia. The third estimated *Equation (1)* using simple TWFE estimation, whereby we only include a single time-varying extended lockdown treatment variable. All three robustness checks produced results similar to those obtained in our baseline analysis. For brevity, these results tests are provided in Appendix 3E along with a more detailed discussion of the findings.

8. Conclusion

8.1 Summary of Findings

Following the lifting of national lockdown in late April and early May 2020, the Australian state governments adopted heterogeneous COVID-19 policies over the course of the second half and 2020 and throughout 2021 (Edwards *et al.*, 2022). Specifically, the states of Victoria, NSW, and ACT implemented extended periods of lockdown, whilst the remaining states only introduced 'snap' lockdowns lasting no more than one-to-two weeks (Li *et al.*, 2023). This heterogeneity in state-level COVID-19 policy provided a quasi-natural experiment setting.

This chapter sought to estimate the causal effects of extended lockdowns on mental health in Australia, and how these effects may be moderated by the Big Five personality traits. We utilised 17 waves of the nationally representative panel data capturing observations on over 180,000 Australian residents in the period of 2005 to 2021. We employed the 'Extended' two-way fixed effects (ETWFE) estimation method proposed by Wooldridge (2021) to allow for the estimation of heterogeneous treatment effects by both cohort and time, and for the assessment of how these effects may be moderated by personality traits.

Our results firstly showed that the extended lockdown of 2020 for residents of Victoria reduced MHI-5 score by 1.470 points relative to those residing in other states. By 2021, MHI-5 score for Victorian residents was estimated to have been reduced by 2.142 points relative to pre-COVID levels. A smaller, but still statistically significant reduction in mental health was experienced by residents of NSW and ACT resulting from their extended lockdowns in 2021. We subsequently found that the personality traits of extroversion, emotional stability, and openness moderated these effects to varying extents. Specifically, we found that extroverts were significantly more susceptible to poorer mental health during extended lockdowns in 2020 and 2021, with this effect most pronounced for residents of Victoria in 2020. Conversely, emotionally stability provided a strong protective effect against the mental health impact of extended lockdowns, with this again being most significant for Victorian residents under the 2020 extended lockdown. Somewhat surprisingly, openness was found to be a significant negative moderator of the effect of extended lockdown, although this was only found in 2020. Neither agreeableness nor conscientiousness were found to be significant moderators.

These results were shown to be generally robust to alternative estimation methods and to various sample restrictions addressing the assumptions of our identification strategy. We further demonstrated that increased policy stringency in general was associated with poorer mental health

and provided further evidence for some personality traits being significant moderators in this relationship.

8.2 Strengths and Limitations

This study has numerous strengths. Firstly, state-level heterogeneity in COVID-19 policy setting in Australia provided an ideal quasi-natural experimental setting to obtain causal estimates of the effect of extended lockdown policies on mental health and how the Big Five personality traits moderated these effects. To the best of our knowledge, this is the first study to investigate this topic using Australian data. The nature of the HILDA data allowed us to explore heterogeneity in both the effect of extended lockdown on mental health, and the moderating effects of the Big 5 personality traits between Victorian residents who experienced extended lockdowns in both 2020 and 2021, and residents of NSW and ACT who experienced extended lockdown in 2021 only. Furthermore, we could examine whether the estimated effects of lockdown and moderating effects of personality traits evolved over time for residents of Victoria.

Our study design improves significantly on existing studies on this topic utilising data from other countries. Firstly, personality was measured at five points in the nationally representative HILDA, with the latest measurement occurring in latest release of the data. This contrasts existing panel data studies with pre-pandemic observations which only measured personality at one time-point nine years prior to the pandemic, and therefore assumed that personality traits of respondents had not changed over time (Proto and Zhang, 2021; Staneva *et al.*, 2022). Furthermore, we were able to define contemporaneous treatment and control groups within our data whereby individuals residing in different states were under varying lockdown conditions at the same point in time. This improves on previous studies on the moderating role of the Big Five personality traits, which have either relied on multinational cross-sectional samples to exploit policy heterogeneity (and only studied the moderating role of extroversion) (Wijngaards *et al.* (2020), used small non-representative samples (Zacher and Rudolph, 2021), stratified by personality traits rather than estimating interaction models (Staneva *et al.*, 2022), or utilised data which lacked a treatment and control group contemporaneously affected and unaffected by lockdown policies (Proto and Zhang, 2021).

However, there remain some limitations with our study. Firstly, a small proportion of respondents were observed outside of the extended lockdown dates, which challenged our identification strategy. Nonetheless, we showed our results were robust to excluding these individuals from the estimation sample. Second, we assumed that extended lockdown was an absorbing treatment in our estimation strategy. Strictly speaking, this was not the case, as residents of Victoria exited

extended lockdown in 2020, before being placed into extended lockdown again in 2021. However, the majority of observations on residents of Victoria occurred during the extended lockdowns, and the state of Victoria also implemented a series of state-wide 'snap' lockdowns in early 2021 prior to the imposition of the extended lockdown. As such, we believe it was reasonable to assume treatment was absorbing in this context. Alternatively, our findings could be interpreted as reflecting the effect of differences in the overarching approach to COVID-19 policymaking between states, as opposed to just the effects of extended lockdowns. We were also unable to control for state-level COVID-19 cases and deaths under the ETWFE framework, as these failed the necessary requirement for covariates to be strictly exogeneous and were incompatible with entropy balancing. In our robustness check using the OxCGRT Stringency Index as an alternative measure of policy stringency, we found that inclusion of COVID-19 cases and deaths reduced the magnitude of the association between policy stringency and mental health. As such, our baseline estimates for the treatment effect of extended lockdown may partially be reflecting the effect of COVID-19 cases and deaths on mental health within the state. Finally, we conducted complete case analysis of the data meaning individuals with any observations missing for one or more variables utilised in the analysis were excluded in a given wave from the analytical sample. Examination of the data suggested this missingness was likely to be missing at random (MAR) meaning our estimates may potentially be biased. To address this, the analysis could be extended by utilising multiple imputation methods to check the robustness of our baseline results.

8.3 Policy Implications and Future Research

Since the lifting of the extended lockdowns in 2021, no states in Australia have re-implemented such measures. As such, rather than guiding COVID-19 policy, the findings of this study should be considered as important for informing future policies should another pandemic occur. This is pertinent given the estimated probability of a future pandemic event of the same magnitude of COVID-19 to occur within the next 25 years is between 47% and 57% (Metabiota, 2021). If such an event were to occur, future governments need to consider whether the public health benefits of lockdown policies outweigh the clear detriment they had to citizens' mental health, as well as other unintended consequences on individuals' lives (Chu *et al.*, 2020; Brodeur *et al.*, 2021b; Chiesa *et al.*, 2021).

Our findings regarding the moderating effects of certain personality traits indicate that if future lockdowns were required, there needs to be tailored support provided to certain groups of individuals who are more susceptible to poorer mental health under these conditions. For example, extroverts may benefit from alternative avenues to access their need for social interactions. It is

likely that future technological advances may aid this, but governments would need to ensure access to such technologies are equitable. Our results also indicated highly neurotic individuals were particularly susceptible to poorer mental health during extended lockdowns. Many individuals with neurotic tendencies may already be known to health professionals due to their proneness to psychological distress. As such, health providers may seek to target such individuals with additional mental health support. Conversely, this finding implies that more emotionally stable individuals fared better under extended lockdowns. Emotionally stability is generally considered to increase over the life course, with Hale *et al.* (2023) postulating that this may explain why older adults exhibited lower falls in their mental health during the pandemic. Given that, at least in the case of COVID-19, older individuals were also the most at risk of hospitalisation or mortality (Dessie and Zewotir, 2021), this suggests that age-targeted lockdowns could prove a more optimal policy approach to protect the health of the most vulnerable whilst minimising unintended mental health effects.

Beyond these policy implications, our findings contribute to the wider literature on how different personality types react to adverse events and may therefore be useful to health and social service professionals in tailoring care to individuals following traumatic events.

An immediate avenue for future research would be to examine the recovery of the mental health of populations as we emerge from the COVID-19 pandemic. In Australia, the forthcoming releases of the HILDA provide an ideal opportunity for this research. Of particular interest should be the exploration of whether different personality types exhibited distinct rates of mental health recovery. Future research may also seek explore additional heterogeneity in the moderating effects of personality traits on mental health during lockdowns, for example through differences in living circumstances or technological literacy.

Chapter Four: Tables and Figures

Table 5.1 Descriptive Statistics

Variable	N	Mean	S.D.	Minimum	Maximum
Dependent Variable					
MHI-5	187,074	73.813	17.336	0	100
Personality					
Extroversion (Normalised)	187,074	0.570	0.180	0	1
Emotional Stability (Normalised)	187,074	0.700	0.180	0	1
Agreeableness (Normalised)	187,074	0.734	0.153	0	1
Conscientiousness (Normalised)	187,074	0.685	0.170	0	1
Openness (Normalised)	187,074	0.536	0.176	0	1
Lockdown Indicators					
Extended Lockdown Cohort 2020	187,074	0.208	0.406	0	1
Extended Lockdown Cohort 2021	187,074	0.236	0.425	0	1
Extended Lockdown	187,074	0.053	0.224	0	1
Cohort 2020: Extended Lockdown 2020	187,074	0.017	0.130	0	1
Cohort 2020: Extended Lockdown 2021	187,074	0.016	0.127	0	1
Cohort 2021: Extended Lockdown 2021	187,074	0.020	0.139	0	1
OxCGRT Variables					
Stringency Index±	24,472	68.496	16.908	27.800	96.300
State COVID-19 Deaths±	24,472	213.705	321.902	0	2,675
State COVID-19 Cases±	24,472	15,086	63,172	33	1,435,768
Greater Capital City Statistical Area					
Greater Sydney	187,074	0.156	0.363	0	1
Rest of NSW	187,074	0.134	0.341	0	1
Greater Melbourne	187,074	0.176	0.380	0	1
Rest of Victoria	187,074	0.071	0.257	0	1
Greater Brisbane	187,074	0.101	0.301	0	1
Rest of Queensland	187,074	0.115	0.318	0	1
Greater Adelaide	187,074	0.066	0.248	0	1
Rest of SA	187,074	0.025	0.157	0	1
Greater Perth	187,074	0.076	0.264	0	1
Rest of WA	187,074	0.019	0.133	0	1
NT	187,074	0.007	0.085	0	1
Tasmania	187,074	0.034	0.181	0	1
ACT	187,074	0.022	0.145	0	1
Individual- and Household-Level Controls					
Male	187,074	0.464	0.499	0	1
Age: 15-24	187,074	0.134	0.341	0	1
Age: 25-34	187,074	0.168	0.375	0	1
Age: 35-44	187,074	0.173	0.379	0	1

Age: 45-54	187,074	0.182	0.386	0	1
Age: 55-64	187,074	0.157	0.364	0	1
Age: 65 and over	187,074	0.183	0.387	0	1
Education Level: Year 12 or Above	187,074	0.742	0.438	0	1
Marital Status: Married	187,074	0.521	0.499	0	1
Marital Status: De Facto Relationship	187,074	0.143	0.349	0	1
Marital Status: Separated	187,074	0.025	0.158	0	1
Marital Status: Divorced	187,074	0.063	0.243	0	1
Marital Status: Widowed	187,074	0.043	0.204	0	1
Marital Status: Never Married	187,074	0.204	0.403	0	1
Labour Force Status: Employed	187,074	0.653	0.476	0	1
Labour Force Status: Unemployed	187,074	0.031	0.173	0	1
Labour Force Status: Not Economically Active	187,074	0.316	0.465	0	1
Real Household Income Per Capita	187,074	29,100 AUD	17,687 AUD	3,538 AUD	106,476 AUD
Log of Real Household Income Per Capita	187,074	10.103	0.604	8.172	11.575
Smoker	187,074	0.171	0.376	0	1
Weekly Drinker	187,074	0.467	0.499	0	1
Self-Rated Health: Poor	187,074	0.031	0.175	0	1
Self-Rated Health: Fair	187,074	0.138	0.345	0	1
Self-Rated Health: Good	187,074	0.365	0.482	0	1
Self-Rated Health: Very Good	187,074	0.358	0.479	0	1
Self-Rated Health: Excellent	187,074	0.107	0.309	0	1
Long-Term Health Condition	187,074	0.285	0.451	0	1
Social Support Index	187,074	54.357	10.183	10	70
Frequency of Social Interaction: Less than Once Every 3 Months	187,074	0.059	0.455	0	1
Frequency of Social Interaction: Once or Twice Every Three Months	187,074	0.065	0.246	0	1
Frequency of Social Interaction: About Once a Month	187,074	0.123	0.328	0	1
Frequency of Social Interaction:	187,074	0.194	0.395	0	1

Two or Three Times a Month					
Frequency of Social Interaction: About Once a Week	187,074	0.314	0.464	0	1
Frequency of Social Interaction: Several Times a Week	187,074	0.214	0.410	0	1
Frequency of Social Interaction: Every Day	187,074	0.030	0.171	0	1
Self-Rated Financial Status: Very Poor	187,074	0.007	0.082	0	1
Self-Rated Financial Status: Poor	187,074	0.025	0.156	0	1
Self-Rated Financial Status: Getting Along	187,074	0.257	0.437	0	1
Self-Rated Financial Status: Reasonably Comfortable	187,074	0.534	0.499	0	1
Self-Rated Financial Status: Very Comfortable	187,074	0.160	0.367	0	1
Self-Rated Financial Status: Prosperous	187,074	0.017	0.129	0	1
Any Negative Event	187,074	0.389	0.488	0	1
Family Relationship: Couple (<65 Years Old) Without Children (<15 Years Old)	187,074	0.293	0.455	0	1
Family Relationship: Couple with Child(ren) (<15 Years Old)	187,074	0.247	0.431	0	1
Family Relationship: Single Parent with Child(ren) (<15 Years Old)	187,074	0.029	0.169	0	1
Family Relationship: Single Parent without Child(ren) (<15 Years Old)	187,074	0.024	0.152	0	1
Family Relationship: Single Person (< 65 Years Old)	187,074	0.104	0.305	0	1
Family Relationship: Elderly Single Person	187,074	0.052	0.222	0	1
Family Relationship: Elderly Couple	187,074	0.119	0.323	0	1
Family Relationship: Dependent Student	187,074	0.047	0.211	0	1
Family Relationship:	187,074	0.058	0.234	0	1

Non-Dependent Child (>15 Years Old)					
Family Relationship: Other Family Member	187,074	0.017	0.130	0	1
Family Relationship: Unrelated to Household Members	187,074	0.010	0.101	0	1
Household Size: Children	187,074	0.562	0.972	0	11
Household Size: Adults	187,074	2.276	1.009	1	10
Index of Relative Social Advantage and Disadvantage (IRSAD)	187,074	5.562	2.854	1	10
Dwelling: Separate House	187,074	0.822	0.382	0	1
Dwelling: Semi/Terrace/Townhouse	187,074	0.067	0.250	0	1
Dwelling: Flat	187,074	0.104	0.305	0	1
Dwelling: Other	187,074	0.007	0.084	0	1
Remoteness Area: Major City of Australia	187,074	0.659	0.474	0	1
Remoteness Area: Inner Regional Australia	187,074	0.225	0.418	0	1
Remoteness Area: Outer Regional Australia	187,074	0.103	0.303	0	1
Remoteness Area: Remote or Very Remote Australia	187,074	0.014	0.116	0	1

Notes: Descriptive statistics are for the baseline sample utilised in the analysis of 187,074 observations on individuals with complete MHI-5 and regressor observations, except for the alternative dependent variables and OxCGRT variables. All figures reported correct to 3 decimal places (except income and COVID-19 cases which are rounded to the nearest whole number).

Figure 5. 1 Mean Mental Health by Extended Lockdown Cohort

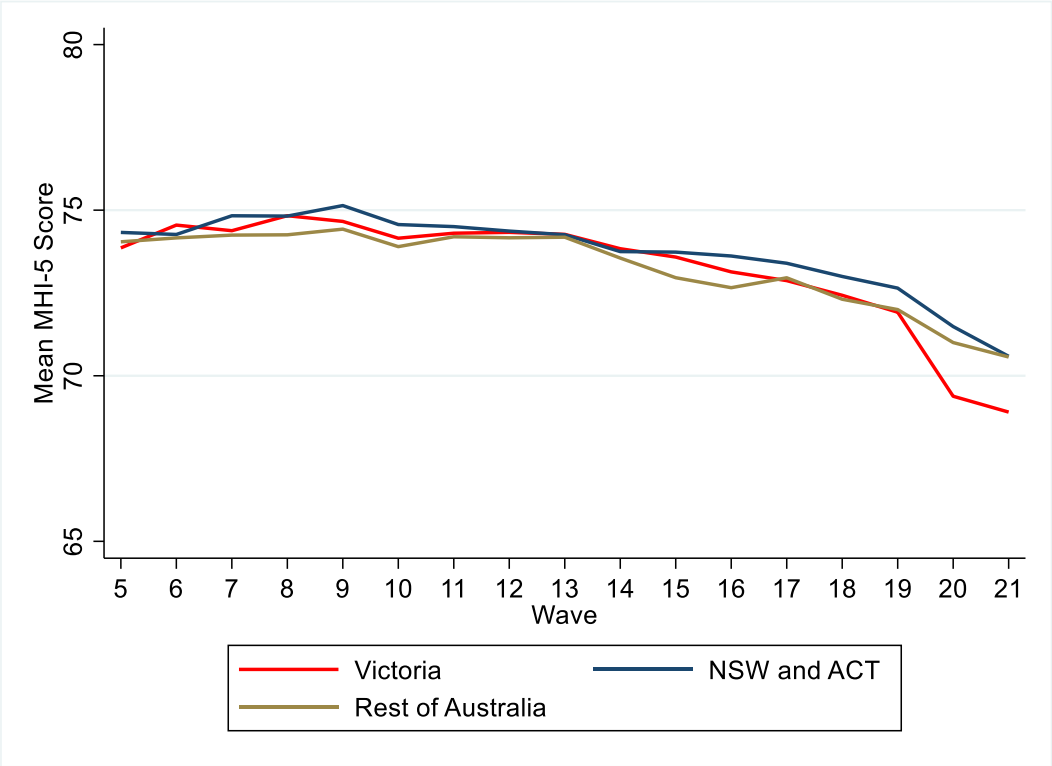


Figure 5.2 OxCGRT Stringency Index in States with Extended Lockdowns

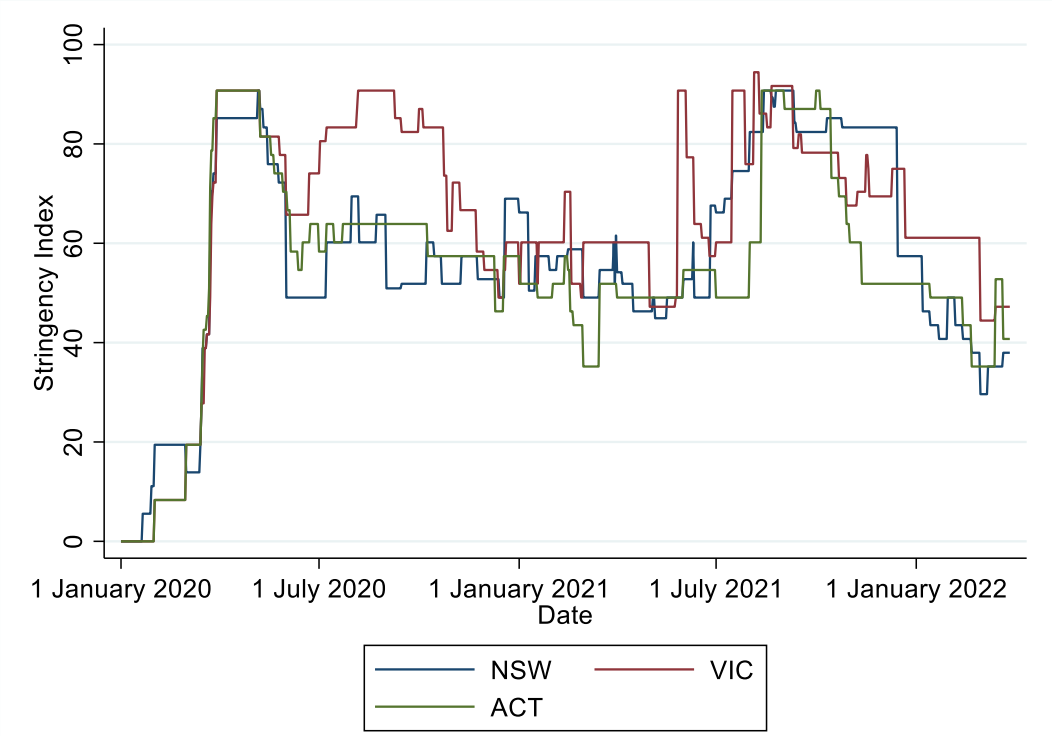


Figure 5.3 OxCGRT Stringency Index in States without Extended Lockdowns

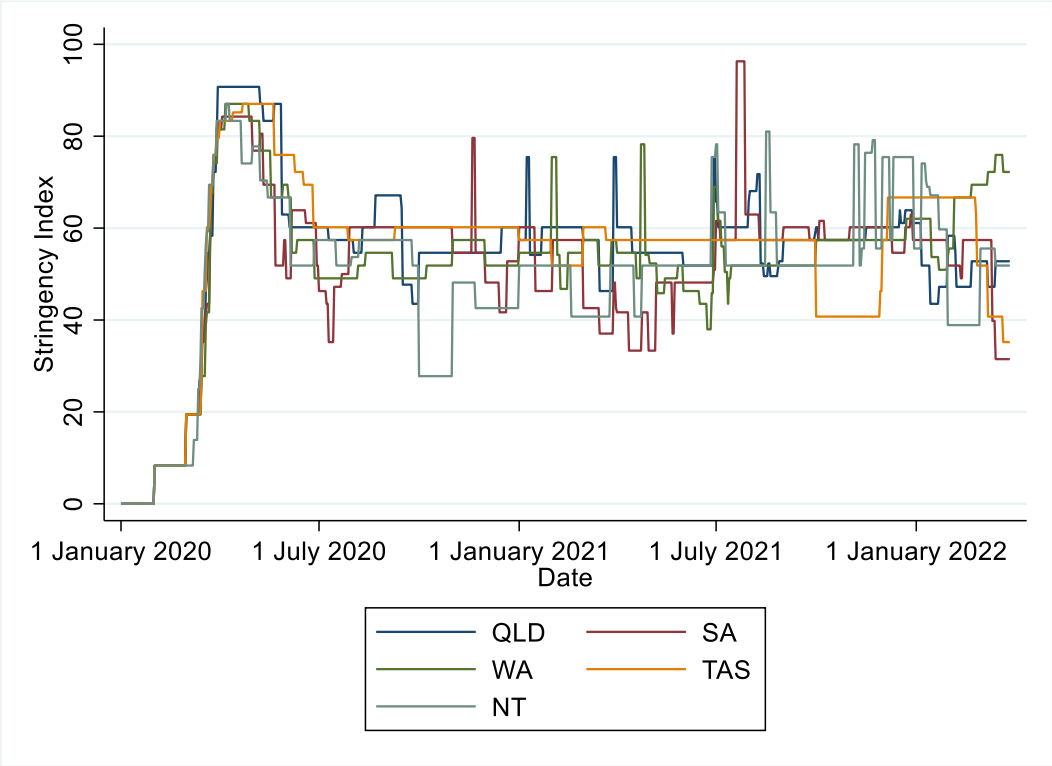


Table 7.1 ETWFE Estimates for the Effect of Extended Lockdown on Mental Health

Variable	(1) No Covariate Adjustment	(2) With Covariate Adjustment
	ATT (t-stat)	**ATT (t-stat)**
D2020 x 2020 Lockdown	-1.692*** (-3.30)	-1.485*** (-3.10)
D2020 x 2021 Lockdown	-2.441*** (-3.39)	-2.140*** (-4.36)
D2021 x 2021 Lockdown	-1.111** (-2.00)	-0.815*** (-2.81)
D2020 Cohort Aggregated ATT	-2.067*** (-3.42)	-1.812*** (-3.95)
All Cohorts Aggregated ATT	-1.748*** (-3.83)	-1.480*** (-4.30)
2021 Lockdown Aggregated ATT	-1.776*** (-3.62)	-1.478*** (4.32)
D2020 x T	Yes	Yes
D2021 x T	Yes	Yes
Personality	No	Yes
Covariates	No	Yes
Personality x D2020 x T	No	Yes
Covariates x D2020 x T	No	Yes
Time Fixed Effects	Yes	Yes
GCCSA Fixed Effects	Yes	Yes
Entropy Balanced	No	Yes
N	187,074	164,841

Notes: ATTs correct to 3 decimal places, t-statistics to 2 decimal places. Statistical significance indicated by * at the 10%, ** at the 5%, and *** at the 1% level. Models estimated using fixed effects regression implemented with the *reghdfe* Stata command. Cluster-robust standard errors are clustered at the GCCSA level. Individual and GCCSA fixed effects are absorbed. Due to the number of interaction terms required for the covariates in the ETWFE method we do not report these results (available on request). The coefficients on the cohort-time interactions are reported in Table C1 in Appendix 3C as these were utilised for the test of the parallel trends assumption. The aggregated ATTs were obtained using the methods shown in *Equations (7)* and *(8)* applied to the cohort-time specific ATTs.

7.2 ETWFE Estimates for the Moderating Role of Personality

Variables	(1) No Covariate Adjustment	(2) With Covariate Adjustment
	ATT (t-stat)	ATT (t-stat)
D2020 x 2020 Lockdown	-1.676*** (-3.23)	-1.502*** (-3.28)
D2020 x 2021 Lockdown	-2.440*** (-3.56)	-2.136*** (-4.47)
D2021 x 2021 Lockdown	-1.124** (-2.17)	-0.847*** (-2.89)
D2020 x 2020 Lockdown x Extroversion	-3.497*** (-3.01)	-4.727*** (-4.50)
D2020 x 2020 Lockdown x Emotional Stability	3.248*** (4.39)	5.071*** (8.07)
D2020 x 2020 Lockdown x Agreeableness	-3.300 (-1.44)	-4.165* (-1.65)
D2020 x 2020 Lockdown x Conscientiousness	1.335 (0.67)	-0.142 (-0.09)
D2020 x 2020 Lockdown x Openness	1.776*** (3.12)	2.441** (2.05)
D2020 x 2021 Lockdown x Extroversion	-2.848** (-2.08)	-2.431** (-2.21)
D2020 x 2021 Lockdown x Emotional Stability	2.322* (1.93)	2.975** (2.37)
D2020 x 2021 Lockdown x Agreeableness	1.057 (0.54)	0.641 (0.26)
D2020 x 2021 Lockdown x Conscientiousness	-1.161 (-0.65)	-1.413 (-0.74)
D2020 x 2021 Lockdown x Openness	0.446 (0.76)	1.995 (1.34)
D2021 x 2021 Lockdown x Extroversion	-1.760 (-1.34)	-1.697 (-1.19)
D2021 x 2021 Lockdown x Emotional Stability	0.387 (0.23)	0.858 (0.41)
D2021 x 2021 Lockdown x Agreeableness	1.102 (0.52)	0.133 (0.06)

D2021 x 2021 Lockdown x Conscientiousness	2.491 (1.11)	3.162 (0.96)
D2021 x 2021 Lockdown x Openness	0.396 (0.26)	0.591 (0.34)
D2020 x T	Yes	Yes
D2021 x T	Yes	Yes
Personality	Yes	Yes
Covariates	No	Yes
Personality x D2020 x T	Yes	Yes
Covariates x D2020 x T	No	Yes
Time Fixed Effects	Yes	Yes
GCCSA Fixed Effects	Yes	Yes
Entropy Balanced	No	Yes
N	187,074	164,841

Notes: ATTs correct to 3 decimal places, t-statistics to 2 decimal places. Statistical significance indicated by * at the 10%, ** at the 5%, and *** at the 1% level. Models estimated using fixed effects regression implemented with the *reghdfe* Stata command. Cluster-robust standard errors are clustered at the GCCSA level. Individual and GCCSA fixed effects are absorbed. Personality traits are demeaned by cohort-time mean when used for DDD estimates. Due to the number of interaction terms required for the covariates in the ETWFE method we do not report these results (available on request).

Table 7.3 Aggregated Cohort ATTs by Personality Trait

Cohort	(1) No Covariate Adjustment	(2) With Covariate Adjustment
	Aggregated ATT (t-stat)	**Aggregated ATT (t-stat)**
D2020 Cohort	-2.057*** (-3.50)	-1.819*** (-4.13)
All Cohorts	-1.746*** (-3.93)	-1.495*** (-4.49)
D2020 Cohort: Extroversion	-3.173*** (-2.82)	-3.579*** (-3.62)
D2020 Cohort: Emotional Stability	2.785*** (3.71)	4.023*** (5.46)
D2020 Cohort: Agreeableness	-1.121 (-0.73)	-1.762 (-0.88)
D2020 Cohort: Conscientiousness	0.087 (0.05)	-0.777 (-0.52)
D2020 Cohort: Openness	1.121 (1.37)	2.218** (2.23)
All Cohorts: Extroversion	-2.702*** (-2.67)	-2.952*** (-3.18)
All Cohorts: Emotional Stability	1.986** (2.42)	2.968*** (3.06)
All Cohorts: Agreeableness	-0.380 (-0.26)	-1.130 (-0.62)
All Cohorts: Conscientiousness	0.888 (0.51)	0.536 (0.29)
All Cohorts: Openness	0.879 (0.90)	1.676 (1.50)

Notes: ATTs correct to 3 decimal places, t-statistics to 2 decimal places. Statistical significance indicated by * at the 10%, ** at the 5%, and *** at the 1% level. The ATTs were obtained using the methods shown in *Equations (7)* and *(8)* applied to the cohort-time specific ATTs presented in Table 7.2.

Table 7.4 The Effect of Extended Lockdown with the Callaway and Sant'Anna Estimator

Cohorts	(1) No Covariates	(2) With Covariates
	ATT **(t-stat)**	**ATT** **(t-stat)**
D2020: 2020 vs 2019	-1.376*** (-4.59)	-1.232*** (-3.80)
D2020: 2021 vs 2019	-2.099*** (-6.08)	-2.202*** (-5.82)
D2021: 2021 vs 2020	-0.489 (-1.62)	-0.314 (-0.93)
Personality	Yes	Yes
Covariates	No	Yes
N	199,963	178,954

Notes: ATTs correct to 3 decimal places, t-statistics to 2 decimal places. Statistical significance indicated by * at the 10%, ** at the 5%, and *** at the 1% level. Models estimated using the Callway and Sant'Anna (2021) estimator implemented through the user-written *csdid* command in Stata 17. For consistency with the EWTFE we utilised both never-treated and not-yet treated observations as controls. By design, *csdid* only uses the last pre-treatment value for any included controls (*i.e.*, personality and covariates), which is why the sample sizes were larger than in the ETWFE which utilises all values of controls provided they are non-missing in any given wave. Cluster-robust standard errors were clustered at the GCCSA level, and individual, time, and GCCSA fixed effects are automatically controlled for. Note the estimator does not provide outputs for the control variables included.

Table 7.5 The Moderating Effect of Personality with the Callaway and Sant'Anna Estimator

Cohort	(1) Low Extroversion	(2) High Extroversion	(3) Low ES	(4) High ES	(5) Low Agree	(6) High Agree	(7) Low Conscient.	(8) High Conscient.	(9) Low Openness	(10) High Openness
D2020: 2020 vs 2019	-0.914* (-1.88)	-1.503*** (-3.40)	-1.359*** (-2.68)	-1.126*** (-2.68)	-0.910* (-1.88)	-1.534*** (-3.47)	-1.261*** (-2.41)	-1.152*** (-2.77)	-1.602*** (-3.27)	-0.937** (-2.13)
D2020: 2021 vs 2019	-1.640*** (-2.59)	-2.086*** (-3.71)	-2.837*** (-3.77)	-1.895*** (-3.58)	-2.099*** (-3.09)	-2.314*** (-3.86)	-2.625*** (-3.67)	-1.576*** (-3.05)	-2.609*** (-4.17)	-2.031*** (-3.39)
D2021: 2021 vs 2019	-0.355 (-0.64)	-0.069 (-0.13)	-0.694 (-1.12)	-0.442 (-0.92)	-0.584 (-0.98)	-0.011 (-0.02)	-1.180* (-1.92)	0.019 (0.04)	-0.504 (-0.87)	-0.627 (-1.18)
Personality	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	77,667	97,640	84,983	89,511	78,196	96,323	80,856	94,192	78,059	96,674

Notes: ATTs correct to 3 decimal places, t-statistics to 2 decimal places. Statistical significance indicated by * at the 10%, ** at the 5%, and *** at the 1% level. Models estimated using the Callway and Sant'Anna (2021) estimator implemented through the user-written *csdid* command in Stata 17. Each model was stratified by 'low' (below median) and 'high' (equal to or above median) on the given personality trait. For consistency with the EWTFE we utilised both never-treated and not-yet treated observations as controls. By design, *csdid* only uses the last pre-treatment value for any included controls (*i.e.*, personality and covariates), which is why the (combined) sample sizes were larger than in the ETWFE which utilises all values of controls provided they are non-missing in any given wave. Cluster-robust standard errors were clustered at the GCCSA level, and individual, time, and GCCSA fixed effects are automatically controlled for. Note the estimator does not provide outputs for the control variables included. Implementation of post-estimation tests for differences between sub-groups is not possible with the *csdid* package.

Table 7.6 The Effect of Extended Lockdown with the CHD Estimator

Lockdown Period	**(1)** **No Covariates**	**(2)** **With Covariates**
	ATT **(t-stat)**	**ATT** **(t-stat)**
Extended Lockdown *t*	-0.934*** (-4.38)	-0.986*** (4.59)
Extended Lockdown *t+1*	-2.291*** (-6.65)	-2.437*** (6.96)
Aggregated ATT	-1.342*** (-6.16)	-1.407*** (-6.42)
Personality	Yes	Yes
Covariates	No	Yes
Sample Sizes	**N Total** **(N Switch)**	**N Total** **(N Switch)**
Extended Lockdown *t*:	21,496 (6,891)	19,121 (6,141)
Extended Lockdown *t+1*:	8,204 (2,927)	7,067 (2,479)
Aggregated ATT	24,648 (9,818)	21,896 (8,620)

Notes: ATTs correct to 3 decimal places, t-statistics to 2 decimal places. Statistical significance indicated by * at the 10%, ** at the 5%, and *** at the 1% level. Models estimated using the de Chaisemartin a and d'Haultfoeuille (2020) estimator implemented with the *did_multiplegt_dyn* Stata command. Standard errors were clustered at the GCCSA level. For the sample sizes, N Total gives the total sample used to obtain the corresponding ATT, with N Switch giving the number of treated observations used.

Table 7.7 The Moderating Effect of Personality with the CHD Estimator

Lockdown Period	(1) Low Extro	(2) High Extro	(3) Low ES	(4) High ES	(5) Low Agree	(6) High Agree	(7) Low Consc	(8) High Consc	(9) Low Open	(10) High Open
	ATT (t-stat)	ATT (t-stat)	ATT (t-stat)	ATT (t-stat)	ATT (t-stat)	ATT (t-stat)	ATT (t-stat)	ATT (t-stat)	ATT (t-stat)	ATT (t-stat)
Extended Lockdown *t*	-0.889*** (-2.65)	-0.939*** (3.10)	-1.303*** (3.61)	-0.944*** (3.27)	-0.927*** (2.69)	-1.212*** (3.99)	-1.423*** (3.94)	-0.870*** (3.01)	-1.095*** (3.18)	-1.198*** (3.92)
Extended Lockdown *t+1*	-1.934*** (-3.28)	-2.157*** (4.16)	-3.061*** (4.68)	-2.049*** (4.12)	-2.564*** (4.16)	-2.426*** (4.43)	-2.513*** (3.87)	-1.914*** (3.93)	-2.883*** (4.90)	-1.860*** (3.45)
Aggregated ATT	-1.164*** (3.36)	-1.269*** (4.13)	-1.739*** (4.61)	-1.245**** (4.23)	-1.337*** (3.80)	-1.533*** (4.87)	-1.727**** (4.68)	-1.149*** (3.92)	-1.562*** (4.49)	-1.137*** (3.62)
Personality	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample Sizes	**N Total (N Switch)**	**N Total (N Switch)**	**N Total (N Switch)**	**N Total (N Switch)**	**N Total (N Switch)**	**N Total (N Switch)**	**N Total (N Switch)**	**N Total (N Switch)**	**N Total (N Switch)**	**N Total (N Switch)**
Extended Lockdown *t*	7,881 (2,431)	9,608 (3,056)	8,202 (2,536)	8,833 (2,756)	7,630 (2,310)	9,497 (3,010)	7,821 (2,396)	9,477 (3,008)	7,836 (2,351)	9,314 (2,947)
Extended Lockdown *t+1*	2,536 (862)	3073 (1,120)	2,402 (826)	2,815 (1,020)	2,303 (764)	2,956 (1,066)	2,416 (821)	3,020 (1,083)	2,485 (822)	2,876 (1,067)
Aggregated ATT	8,832 (3,293)	10,852 (4,176)	9,134 (3,362)	9,959 (3,776)	8,500 (3,074)	10,659 (4,076)	8,785 (3,217)	10,651 (4,091)	8,775 (3,173)	10,483 (4,014)

Notes: ATTs correct to 3 decimal places, t-statistics to 2 decimal places. Statistical significance indicated by * at the 10%, ** at the 5%, and *** at the 1% level. Models estimated using the de Chaisemartin a and d'Haultfoeuille (2020) estimator implemented with the *did_multiplegt_dyn* Stata command. Standard errors were clustered at the GCCSA level. For the sample sizes, N Total gives the total sample used to obtain the corresponding ATT, with N Switch giving the number of treated observations used. 'Extro' is extroversion, 'ES' is emotional stability, 'Agree' is agreeableness, 'Consc' is conscientiousness, 'Open' is openness.

Table 7.8 Fixed Effects Regression with OxCGRT Variables with Moderating Effects

Variable	(1) No Deaths or Cases	(2) With Deaths and Cases
	Coefficient (t-stat)	Coefficient (t-stat)
OxCGRT Stringency	-0.045*** (-3.55)	-0.030*** (-3.02)
Extroversion	5.328*** (13.02)	5.320*** (12.90)
Emotional Stability	8.225*** (21.95)	8.228*** (21.67)
Agreeableness	1.708*** (5.12)	1.706*** (5.09)
Conscientiousness	0.975 (1.62)	0.974 (1.61)
Openness	0.915 (1.57)	0.905 (1.56)
Extroversion x OxCGRT Stringency	-0.005 (-0.64)	-0.005 (-0.61)
Emotional Stability x OxCGRT Stringency	0.019*** (4.87)	0.020*** (4.96)
Agreeableness x OxCGRT Stringency	-0.026*** (-3.34)	-0.025*** (-3.27)
Conscientiousness x OxCGRT Stringency	0.025*** (2.93)	0.023*** (2.78)
Openness x OxCGRT Stringency	0.005 (0.82)	0.005 (0.92)
State COVID-19 Deaths	-	-0.002** (-2.33)
State Covid-19 Cases	-	0.000 (0.69)
Covariates	Yes	Yes
Time Fixed Effects	Yes	Yes
GCCSA Fixed Effects	Yes	Yes
Entropy Balanced	No	No
N	187,074	187,045

Notes: ATTs correct to 3 decimal places, t-statistics to 2 decimal places. Statistical significance indicated by * at the 10%, ** at the 5%, and *** at the 1% level. Models estimated using fixed effects regression implemented with the *reghdfe* Stata command. Cluster-robust standard errors were clustered at the GCCSA level. Individual and GCCSA fixed effects are absorbed. Results for the control variables are available on request.

Chapter Five: Conclusion

1. Summary of Findings

The thesis encompassed three empirical studies focusing on the impact of various shocks on mental health and subjective wellbeing (SWB). In chapter two, we explored the associations between self-reported household shocks, food insecurity, and conflict, on the one hand, and life satisfaction, on the other, in Tanzania. In chapter three, we investigated the impact of a tobacco sales ban on depressive feelings of smokers in South Africa. In chapter four, we examined the consequences of extended lockdown policies on mental health in Australia. These studies provided valuable insights into the multifaceted relationships among different shocks, mental health outcomes, and SWB across diverse contexts. Additionally, they shed light on groups susceptible to, or protected from, these effects.

Chapter two employed two waves of individual-level panel data from the Tanzanian Household Panel Survey (TZNPS) and data from the Armed Conflict Location and Event Data (ACLED) Project. This research was motivated by the dearth of methodologically rigorous studies in Sub-Saharan Africa on the intertwined relationships between shocks, conflict, food insecurity, and SWB. As such, we first estimated models to explore the direct effect of self-reported shocks conflict, and food insecurity on life satisfaction, before conducting moderating and mediating analyses to explore connections in the relationships. The findings revealed that only certain self-reported shocks significantly correlated with reduced SWB, primarily those which were more idiosyncratic to households and more likely to affect all individuals within households, such as severe illness of a household member or death of a family member. We also found increased conflict intensity and food insecurity were negatively associated with life satisfaction. Moderation analyses revealed that individuals reporting food insecurity were more vulnerable to diminished wellbeing when facing labour market shocks, while those receiving financial or food aid were shielded from adverse effects. Furthermore, the negative association between incidence of food insecurity and life satisfaction was more pronounced among individuals in the upper quartile of the consumption distribution, within which food insecurity was less prevalent. This suggested that the cross-national findings of Elgar *et al.* (2021) that food insecurity exhibits a greater negative effect in countries with lower food insecurity rates may be applicable to within-country settings, potentially reflecting a greater stigmatisation of food insecurity or less favourable social comparisons for food insecure individuals of higher socioeconomic status. Finally, mediating analyses indicated that food insecurity and consumption were not significant mediators in the

relationships between shocks, conflict, and SWB, suggesting that, where statistically significant, these events primarily exerted a direct influence on life satisfaction.

In chapter three we examined the impact of the tobacco sales ban, implemented by the South African government in response to the COVID-19 pandemic, on the frequency of depressive feelings among smokers. We analysed eight waves of panel data drawn from the South African National Income Dynamics Survey (NIDS) and the NIDS Coronavirus Rapid Response Mobile Survey (NIDS-CRAM) to address this under-researched area regarding the ban's unintended mental health consequences. Using triple difference-in-difference (DDD) estimation, the study found that pre-ban smokers who continued to smoke during the ban experienced elevated frequencies of depressive feelings, while the mental health of those who quit did not significantly differ from non-smokers during the ban. Given evidence that most smokers attempted to quit but were ultimately unsuccessful, we postulated that the so-called 'struggling quitters hypothesis' may have been a key mechanism behind this finding. Furthermore, a gender-based analysis revealed that only female pre-ban smokers exhibited significantly elevated depressive feelings during the ban. We linked this finding to previous research indicating that women are more likely to smoke to alleviate negative emotions and are generally less successful in cessation attempts.

In chapter four, we exploited state-level heterogeneity in COVID-19 policies in Australia to estimate the impact of extended lockdowns on mental health. We further investigated how the 'Big Five' personality traits moderated these effects. This study utilised 17 waves of data from the Household, Income, and Labour Dynamics Australia (HILDA) survey, encompassing over 180,000 observations on individuals between 2005 and 2021. To account for variations in the timing and implementation of extended lockdown policies, we applied the 'Extended' two-way fixed effects (ETWFE) estimation method to obtain causal estimates of these effects which were allowed to vary across cohorts and time (Wooldridge, 2021). The results indicated that individuals residing in states that implemented extended lockdown policies in 2020 and 2021 experienced significant declines in mental health. The most pronounced effect was observed among residents of Victoria during their extended lockdown in the latter half of 2020. Furthermore, the study revealed that three of the Big Five personality traits significantly moderated these relationships. Highly extroverted individuals were notably more susceptible to deteriorating mental health during extended lockdowns than highly introverted individuals, although this moderating effect somewhat diminished between the 2020 and 2021 extended lockdowns. Additionally, individuals with high levels of emotional stability were largely protected from the mental health effects of extended lockdowns, as were, to a lesser extent, individuals who scored higher on openness to experience, with this latter effect dissipating in 2021. This somewhat surprising results concerning

openness to experience may reflect that more open individuals initially appraised the extended lockdown in 2020 as a new opportunity to embrace their innate creativity and for personal growth, with the novelty subsiding by 2021.

2. Policy Implications

A key policy implication arising from chapter two is the importance of financial and other forms of assistance in safeguarding the wellbeing of individuals confronted with labour market shocks. This outcome aligns with results from studies in other nations which have illustrated social security nets and remittances can play a protective function in protecting the welfare of individuals (Harrower and Hoddinott, 2004; Bene *et al.*, 2012; Alem and Kohlin, 2014). Together, these findings illustrate the need for social safety nets in countries with populations that are especially vulnerable to different shocks. Furthermore, our study provided evidence that even relatively minor increases in conflict events produced detectable changes in individuals' SWB. This discovery underlines a critical concern for the future: the potential consequences of climate change leading to heightened resource scarcity, which could escalate tensions among communities and trigger civil unrest (Blocher and Kileli, 2020; Bergius *et al.*, 2020). This issue of future resource scarcity may be further compounded by the rapid population growth projected for Tanzania, with estimates indicating a doubling of the population by 2035 (Mwakisisile and Mushi, 2018). This emphasises the global need to address climate change, as its effects will reverberate not only in Tanzania but throughout Sub-Saharan Africa, and the potential resulting large-scale conflict events would undoubtedly have devastating repercussions for the wellbeing of citizens.

Despite chapter three being a retrospective analysis of a now-lifted policy, our findings carry significant policy implications. Primarily, they illustrated the ineffectiveness of outright tobacco product prohibition as a viable policy option. As demonstrated by studies examining the market and behavioural impact of the ban, such prohibitions had minimal influence on smoking prevalence. Instead, they fostered the growth of the illicit tobacco market and led to substantial losses in potential excise revenue (van Walbeek *et al.*, 2020; van der Zee *et al.*, 2023; van Walbeek *et al.*, 2023). Furthermore, the ban inadvertently inflicted harm on the mental health of smokers, who were denied access to cessation support while it was in place. We therefore proposed that policymakers should consider market-based approaches to reduce smoking rates, such an increased excise duty, as advocated by other researchers (van Walbeek *et al.*, 2020; van der Zee *et al.*, 2023; van Walbeek *et al.*, 2023). However, governments should concurrently ensure accessible and affordable smoking cessation support for individuals attempting to quit, which was notably absent during the ban. Neglecting this aspect could subject relapsing smokers to negative mental health consequences, as suggested by the 'struggling quitters hypothesis'.

Chapter four contributed to the growing body of evidence emphasising that, whilst effective in curbing the transmission of COVID-19 and subsequent hospitalisations and fatalities, the implementation of extended lockdowns can have profound adverse effects on individuals' mental health. Although the immediate threat of COVID-19 has diminished, these findings retain their relevance for policymakers in the event of future pandemics. Given the non-negligible probability of future pandemics (Metabiota, 2021), governments must weigh the pros and cons of lockdown policies carefully. Additionally, our research indicates that in the event of lockdowns becoming necessary again, there would be a need for tailored support for individuals with different personalities. Extroverts may benefit from alternative avenues to access desired social interactions, potentially through technological means. Equitable access to these technologies is imperative. Mental health service providers should also be prepared to offer additional support to individuals with high neuroticism, who may likely already be known to them. Finally, given that emotional stability tends to increase with age (Hale *et al.*, 2023), it may be pertinent for governments to consider future lockdowns to be targeted at older age groups. In the case of COVID-19, this would have protected individuals who were most susceptible to severe complications or mortality, whilst minimising the mental health effects on younger individuals.

3. Strengths and Limitations

The study conducted in chapter two has several strengths. Firstly, it leveraged two waves of panel data enabling the application of more robust econometric techniques to previous studies of SWB using Tanzanian data. The use of the ordered Probit estimator with Mundlak-style corrections allowed for the calculation of Average Marginal Effects (AMEs) which provided deeper insights into the impact of shocks, conflict, and food insecurity on life satisfaction. This provided a substantial advancement from previous cross-sectional studies. Moreover, the CII provided a more precise assessment of conflict's impact on SWB compared to previous studies. We added further depth to the study through moderation and mediation analyses, exploring subgroup vulnerabilities to the SWB impacts of shocks, conflict, and food insecurity, and assessing indirect relationships between shocks and conflict with life satisfaction through food insecurity and consumption using general structural equational models (GSEM). Finally, the estimated models included various socioeconomic and demographic control variables, therefore making a significant contribution to the wider literature on SWB determinants in Tanzania.

However, this study was not without limitations. Firstly, we were unable to use the first wave and fourth waves of the TZNPS. A longer panel would have been beneficial to provide more observations on the self-reported household shocks. Another limitation concerns the nature of the variables we used. For instance, we could not determine whether a shock was genuinely

unexpected. Furthermore, shocks were reported at the household level, while individual SWB was measured at the individual level, potentially missing the varying impact of shocks on individuals within households. The self-reported food insecurity variable was also less comprehensive than in other studies, lacking severity or frequency information. Additionally, while we improved upon prior literature by using the CII to measure conflict, this did not differentiate between different types of conflict event. Lastly, although we employed estimation methods to control for individual-level time-invariant heterogeneity, we could not establish causality in the estimated relationships between the self-reported shocks and SWB. Further, although our conflict variable was exogenous, it exhibited relatively low variation in the study period.

The study in chapter three therefore improved methodologically on chapter 2 by leveraging a quasi-natural experimental setting and longitudinal panel data to estimate the 'treatment' effect of a policy shock, the tobacco sales ban, on the mental health of smokers. We further enhanced this design by employing entropy balancing to reweight the control group of non-smokers in our sample so that they near-identically matched smokers on observable characteristics. Overall, this significantly improved on the only previous study on the mental health effect of the ban which relied on qualitatively findings. Using this estimation strategy, we obtained causal estimates indicating continuing smokers and female smokers exhibited increased frequencies of depressive feelings during the ban.

However, there remained limitations with the study. Most notably, depression data was not available in first NIDS-CRAM wave, which was conducted during the early weeks of the ban. This prevented us from exploring how the ban's mental health effects on smokers evolved over time. Furthermore, we could only use a single question regarding frequency of depressive feelings rather than a full depression index, as the NIDS and NIDS-CRAM administered different measures.

Finally, the study in chapter four provided the most robust analysis into how shocks may affect mental health. The HILDA data utilised provided observations on over 180,000 individuals and included multiple validated measures of mental health and wellbeing. Furthermore, the state-level heterogeneity in COVID-19 policy setting in Australia provided an ideal quasi-natural experimental setting to estimate the moderating effects of the Big Five personality traits on the impact of extended lockdown policies on mental health. This provided a significant improvement on previous studies in the literature as we could define groups which were contemporaneously affected and unaffected by extended lockdown within the same country. We further employed a ETWFE methodology which allowed causal estimates to be obtained using standard regression methods whilst still accounting for the staggered treatment design. The study therefore not only

provided the most robust analysis of the moderating effects of personality traits during lockdowns to our knowledge, but also contributed to the wider literature by providing estimates for how the effect of lockdown policies may change over time.

Nevertheless, this study still had some limitations. First, a small proportion of respondents fell outside the extended lockdown dates, posing challenges to our identification strategy. However, we demonstrated the robustness of our results when excluding these individuals from the estimation sample. Second, we could not control for state-level COVID-19 cases and deaths within the ETWFE framework due to issues with endogeneity and the compatibility of these variables with entropy balancing. In a robustness check using the OxCGRT Stringency Index, we found that including COVID-19 data reduced the magnitude of the association between policy stringency and mental health, suggesting that our baseline estimates for the extended lockdown effect may partially reflect the impact of COVID-19 cases and deaths on mental health within the state.

4. Future Research

While this thesis has provided valuable insights into the complex connections between shocks, mental health, and SWB across diverse contexts and populations, there remain several avenues for future research.

With regards to chapter two, our comprehension of the effects of shocks, food insecurity, and conflict on SWB would greatly benefit from the expansion of individual-level panel surveys in Sub-Saharan Africa. Although numerous Living Standards Measurement Surveys (LSMS) are conducted in the region and contain data on self-reported shocks similar to those used in our study, only the TZNPS has incorporated SWB measures. Expanding these surveys to encompass measures of SWB and mental health would facilitate further investigation into the impact of shocks, conflict, and food insecurity on SWB across a wide range of settings, promoting meaningful cross-country comparisons.

For chapter three, our findings led to the conclusion that outright prohibition should not be a favoured policy choice for governments seeking to reduce smoking prevalence among their populations. Other authors have advocated for market-based policies like increases in excise duties (van Walbeek *et al.*, 2020; van der Zee *et al.*, 2023; van Walbeek *et al.*, 2023). Future research should explore the effectiveness of such policies while also considering the potential consequences they may have on mental health if adequate cessation support is not provided. Indeed, it is plausible that imposing a higher financial cost on smoking alone may not suffice as a deterrent and could potentially lead to inequitable impacts, especially if individuals from low-income backgrounds continue to smoke at the expense of consumption of other goods. Another intriguing policy

development is the New Zealand government's decision to gradually make tobacco purchase illegal by birth year (New Zealand. Ministry of Health, 2022). Future research could delve into the repercussions of this policy, not only regarding its impact on smoking rates but also on any unanticipated negative effects.

In the context of chapter four, an immediate avenue for future research would involve examining the recovery of the mental health of populations as we emerge from the COVID-19 pandemic. In Australia, the forthcoming releases of the 2022 and 2023 HILDA datasets in the next two years present an ideal opportunity for such investigations. Of particular interest will be whether individuals with different personality types exhibit distinct rates of mental health recovery following the lifting of lockdown policies.

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Appendices

Appendix 1: Chapter Two

Appendix 1A: Summary of Findings from the Literature Review

Table A1: Literature on the Non-Shock Determinants of Subjective Wellbeing

Author(s)	Country	Data	SWB Outcome	Methods	Key Findings
Kabote (2018)	Tanzania	Cross-section of 180 female entrepreneurs and non-entrepreneurs from the Arumeru district, collected by author (no date given)	Personal Wellbeing Index (PWI) – score of 0 to 70	OLS regression	Entrepreneurship and age positively associated with wellbeing, being married negatively associated with wellbeing. Years of schooling, employment status, wealth, and household size coefficients are not significant.
Mwanyangala *et al.* (2010)	Tanzania	Cross-section of 2,463 men and 2,668 women aged 50 and over from the town of Ifakara, collected by authors in 2007	Quality of Life measured through 8-item WHOQoL instrument – transformed in index of 0 to 100	OLS regression	Being a woman, single, and from the lowest and second lowest socioeconomic quartile are associated with greater odds of having below-median quality of life. The odds of having below-median quality of life also increase with each age group relative to those aged 50-59. Education was not found to be a significant determinant of QoL.
Nanor *et al.* (2021)	Ghana	Cross-section of 320 households from 10 rural villages along the Kubease-Juaben feeder road, collected by authors in 2019	Happiness with life measured on an 11-point scale (reduced to 4 categories of 'not happy', 'fairly happy',	Bivariate correlations firstly examined to build subsequent ordered probit model	Individuals ranked transportation as the most important domain in contributing to their happiness, followed by health, education, economics, housing, environment, and finally neighbourhood safety. The bivariate analysis indicated that 15 variables in total displayed a significant correlation with SWB. These 15 variables were then used in a stepwise OLS regression to determine the factors for use in the final ordered probit model. Of these, seven were selected: religious background, source of employment, usage of health facility, registration for and National Health Insurance

			'happy', and 'very happy')		Scheme (NHIS) card, number of dependents, major source of water. The results showed the youngest age group (15-25) had the highest probability of reporting being unhappy, those who reported using a health care facility were less likely to be happy than those who did not, those who had an NHIS card were more likely to be happy than those who did not, respondents with access to water from a well were 45% more likely to report being happy than those who accessed water from a mechanised borehole, those employed in crop farming found to be the most likely to be happy in the sample, and finally Muslims were found to be significantly more likely to be happy than Christians and other religions.
Blaauw and Pretorius (2013)	South Africa	Cross-section of 13,792 individuals from the NIDS (2008 wave)	Life Satisfaction – scale of 1 to 10	OLS and ordered probit regression	Age exhibits U-shape relationship with life satisfaction. White, Coloured, and Asian positively associated with life satisfaction relative to Africans. Marriage, number of children, years of schooling, household income per capita, BMI, and importance of religion positively associated with LS. Being female is negatively associated with LS.
Bookwalter and Dalenberg (2004)	South Africa	Cross-section of 5,190 individuals from the SALDRU (collected in 1994)	Life Satisfaction – scale of 1 to 5	Ordered probit regression stratified by expenditure quartile	Determinants of LS vary by expenditure quartile. Poorest quartile: better housing and sanitation and reduced reliance on public transport associated with higher LS. Second poorest quartile: ownership of durable goods also significantly associated with higher LS. Second richest quartile: Greater education also significantly associated with higher LS. Richest quartile: housing and public transport non-significant, health, education, expenditure, durable assets significantly associated with higher LS.
Kannemeyer (2016)	South Africa	Panel of 34,634 observations on individuals from the NIDS (first four waves from 2008 to 2014/15)	Life Satisfaction – scale of 1 to 10	Random effects linear regression	Perceived neighbourhood disorder, CES-D 10 score, living in urban informal or tribal areas relative to urban formal areas, and being an African male or African female relative to a White male all negatively associated with LS. Household income per capita, perceived SES, employment, marriage, better SRH, and being a Coloured woman relative to White male positively associated with LS. Age exhibits U-shaped relationship with LS.
Ting *et al.* (2017)	South Africa	Panel of 31,319 observations on	Life Satisfaction –	Conditional ordered logit	Transitory income (proxied by climatic variables) positively associated with saving, as is permanent income (proxied by

		individuals from NIDS (first four waves from 2998 to 2014/15) Temperature and precipitation data from 1979-2014 from European Centre for Medium-Range Weather Forecasts	scale of 1 to 10	(BUC) regression	sociodemographic characteristics). Increased saving induced by an increase in transitory is positively associated with LS. Saving induced by permanent income increases are not associated with LS.
Ngamaba (2017)	Multinational	85,070 observations from the World Value Survey collected between 2010 and 2014	Life satisfaction on a 10-point scale, happiness on a 4-point scale	Descriptive analysis and multi-level regression	Descriptive analysis showed Latin America has the highest levels of SWB of all regions, whilst Eastern Europe and the Former Soviet Union, and the Middle East and North Africa have the lowest levels of SWB. In terms of the countries in Sub-Saharan Africa, Nigeria and Ghana have the highest levels of SWB (ranked 10th and 11th respectively), followed by Rwanda (ranked 17th), then Zimbabwe (ranked 23rd), and finally South Africa (ranked 32nd). The results from the multi-level regressions for happiness and life satisfaction indicate the most significant factors drivers of SWB are health, financial satisfaction, income ranking, freedom of choice, trust, national pride, importance of friends and family, leisure, being female, weekly religious attendance, GDP per capita, and income inequality.
Nicola *et al.* (2018)	Ecuador	21,265 heads of house from the 2015 National Survey on Employment, Unemployment, and Underemployment	Life satisfaction on an 11-point scale	Multi-level regression	At the individual level, being male, education, employment, income, religion, leisure time, higher institutional trust, access to health insurance, homeownership, structural integrity of walls, and internet access positively associated with life satisfaction. Being from an indigenous minority negatively associated with life satisfaction. Age exhibits U-shaped relationship with turning point estimated at 70 years old (age of retirement). At the canton-level, oil dependency and non-oil GVA per capita are negatively associated with life satisfaction.

Howell and Howell (2008)	Multinational	Meta-analysis of 111 samples drawn from 56 developing countries 102,224 observations on individuals from 54 developing countries from the 1990, 1995, and 2000 waves of the World Values Survey	Various including overall life or domain-specific satisfaction, happiness, and affect. Life satisfaction on a 10-point scale, happiness on a 4-point scale	Meta-analysis Pooled repeated cross-sectional regression	The positive relationship between economic status and SWB was strongest in low-income developing countries, and in samples with lowest average levels of education. Relationship between SWB and economic status strongest when SWB was measured through life satisfaction, and when economic status was measured through wealth as opposed to income. Estimated coefficients from the analysis of the World Values Survey generally replicated those from the meta-analysis.
Sarracino (2010)	Multinational	6,450 observations on individuals from low-income countries, and 3,467 observations from individuals in high-income countries obtained from four waves of the WVS (from 1980 to 2000)	Life satisfaction on a 10-point scale	OLS regression on the two samples	Income and relative income positively associated in both high and low-income countries, with stronger associations in the latter. SWB positively associated with time spent with colleagues from work or people from religious environments in LICs, whilst in HICs SWB is additionally positively associated with time spent in sporting or other recreational organisations, and with relatives or friends. The strongest positive association found between a relational good and SWB in LICs is participation in political or professional organisations. Social capital indicators are also found to be positively associated with SWB both in LICs and HICs, with the size of the social capital coefficients almost double in HICs than LICs. Unemployment is found to be significantly negatively associated with SWB in both country types, with a much larger (in absolute magnitude) negative coefficient estimated for HICs. Age exhibits the expected U-shaped relationship with SWB, although the turning point is slightly later on in life for HICs (approximately 58 years old versus approximately 52 years old).

Table A2: Summary of Literature on the Relationship between Shocks and Subjective Wellbeing

Author(s)	Country	Data	Subjective Wellbeing Outcome	Self-Reported Shock(s)	Methods	Shock Findings	Other Findings
Jiao *et al.* (2019)	Tanzania and Kenya (Serengeti-Masa Protected Area)	Cross-section of 985 households	Wellbeing Index, comprised of five domains 'Basic Materials for a Good life', 'Security', 'Health', 'Good Social Relations', and 'Freedom of Choice and Action'	Number of negative (unspecified) shocks experienced by household	OLS	Number of shocks negatively associated with wellbeing index, and with all sub-domains except 'Good Social Relations). Other outcomes are also considered. Number of shocks experienced negatively associated with environmental income and environmental reliance.	Distance to protected area and household education positively associated with overall WBI, and the basic materials, health, and freedom of choice wellbeing domains. Household head education also positively associated with safety domain.
Jansen *et al.* (2015)	South Africa	Cross-section of 16,883 individuals from NIDS (2010/11 wave)	Life Satisfaction (binary variable equals 1 if 4 or below on scale of 10)	Binary variable for experiencing at least one of 12 shocks in past year. Perception of likelihood of being a victim of crime in neighbourhood.	Probit regressions	Experience of negative events is unexpectedly associated with lower probability of reporting low life satisfaction. Higher perception of likelihood of being victim of crime associated with greater probability of reporting low life satisfaction. Other outcomes are also considered. Negative events variable negatively associated with self-perceived relative welfare and self-perceived relative poverty, but not associated with objective poverty outcomes.	Living in an urban area, being a discourage job seeker, being unemployed, and number of children associated with higher probability of reporting low life satisfaction. Public asset index (water, sanitation etc.), private asset index (durable goods), being Coloured, White, or Asian relative to African ethnicity, having high school education or above, being a permanent employee, having excellent, very good, good, or fair SRH relative to poor, stating religion is important or very important, being a member of a group or society, being

							covered by medical aid, and the number of elderly household members are all associated with lower probability of reporting low life satisfaction.
Moller (2005)	South Africa (Nelson Mandela Metropolitan Municipality)	Cross-section of 3,300 households collected in 2002	Life satisfaction	Victimisation of crime	Stepwise OLS regressions	Being a victim of crime negatively associated with life satisfaction, although associated is crowded out by fear of crime variable when included in the regression model.	Being a shack dweller, unemployed, and a non-member of a local organisation associated with lower life satisfaction. Owning a telephone, being a homeowner, identifying there is no unsafe place in the neighbourhood, personal wellbeing index, domain satisfaction index, and neighbourhood quality of life index are positively associated with life satisfaction.
Alem and Kohlin (2014)	Ethiopia	Cross-section from EUSS Panel (2008/9 wave)	Life satisfaction (5 point scale)	Self-perceived impact of food price inflation	Ordered Probit	Negative association between food price inflation and life satisfaction. 'Very negatively affected' and 'negatively affected' households more likely to report being 'very dissatisfied' or 'dissatisfied', and less likely to report being 'satisfied' than those who stated they were 'not at all' affected by food price inflation.	Consumption per AEU, reporting that they are currently living better than 5 years ago, expecting a better life in the future, receiving international remittances positively associated with life satisfaction. Being relatively poor, reporting that they are currently living worse than 5 years ago, expecting a worse life in the future, and being single or divorced negatively associated with life satisfaction.
Reyes-Garcia *et al.* (2015)	23 countries across Asia, Africa, and	Cross-section of	Overall life satisfaction (5-point scale)	Dummy variables for recent	Ordered logistic regression	Major loss of crops and/or livestock and household death or illness are significantly	Absolute income positively associated with life satisfaction, being economically worse off

	Latin America	6,793 rural households		unemployment, household death or illness, and major loss of crops and/or livestock		negatively associated with life satisfaction. Estimated coefficient for household illness or death is nearly double that for major loss of crops and/or livestock (-0.350 to -0.410 vs -0.189 to -0.252). Recent unemployment not significantly associated with life satisfaction.	(better off) than five years ago negatively (positively) associated with life satisfaction, being perceived to be worse off (better off) than neighbours negatively (positively) associated with life satisfaction, relative income positively associated with life satisfaction. Household size and being married positively associated with life satisfaction, gender, age, and education not found to be significantly related to life satisfaction.

Table A3: Summary of Literature on the Relationship between Food Insecurity and Subjective Wellbeing

Author(s)	Country	Data	Subjective Wellbeing Outcome	Food Insecurity Measure	Methods	Food Insecurity Findings	Other Findings
Frongillo *et al.* (2017)	Multinational (138 countries)	132,618 observations from the 2014 Gallup World Poll	Current and expected life evaluation on scale of 0 to 10 used to define cut-offs for 'thriving', 'struggling', and 'suffering. Daily experience index constructed from positive and negative experience indices (PEI and NEI)	Food Insecurity Experience Scale (FIES)	Multinomial regression for life evaluation, linear regression for daily experience index	Food insecurity found to be the largest significant negative predictor for both life evaluation and daily experience index. Size of the negative coefficients for food insecurity measures increased (in absolute terms) with each classification from low- to high-income countries for both wellbeing measures. wellbeing.	Other significant negative predictors of both measures of SWB were being divorced or separated, widowed, lacking adequate shelter or housing, and being in part-time employment whilst wanting to work full time. Positive predictors of both measures include having instrumental and emotional support, whilst being female, having secondary school education or higher, and living in a large city were also found to be positively associated with life evaluation only.
Elgar *et al.* (2021)	Multinational (160 countries)	928,043 observations from annually repeated cross-section of Gallup World Poll (2014-2020)	Life evaluation on a scale of 0 to 10. Positive wellbeing measured by PEI, NEI taken as measure of mental health	FIES – raw score used for absolute food insecurity measure, and to derive a relative food insecurity measure in conjunction with the Yitzhaki index	Censored Tobit regression for life evaluation, Poisson regression for PEI and NEI	Absolute and relative food insecurity negatively associated with life evaluation and PEI, and positively associated with NEI. For life evaluation and NEI, absolute food insecurity is more strongly associated in countries where food insecurity was more prevalent at national level, and relative food insecurity more strongly associated when food insecurity was less prevalent at	N/A

						national level. Latter result is also found for PEI.	
Na *et al.* (2018)	39 sub-Saharan African Countries (including Tanzania)	102,235 observations from annually repeated cross-section of Gallup World Poll (2014-2016)	PEI and NEI (note the authors take these as measures of mental health rather than subjective wellbeing)	FIES – four groups defined using raw score (0, 1-3, 4-6, 7-8)	Univariate and multivariate linear regressions	Increasing severity of food insecurity associated with higher NEI score and lower PEI score. A modifying effect for social support and food insecurity was found – the beneficial impact of social support was found to be significantly greater for those in the most severe food insecurity group.	NEI (PEI) scores were lower (higher) across all food insecurity groups for those with perceived, integrative, and emotional support. The PEI score was higher for those with foreign perceived social support, whilst there was no significant difference found for either index for received or given social support.
Asfahani *et al.* (2019)	19 Arab Countries	8,162 observations from annually repeated cross-section of Gallup World Poll (2014-2015)	Life evaluation score on scale of 0 to 10. PEI and NEI combined into daily experience index	FIES – moderate and severe food insecurity defined through FAO thresholds	Multivariate linear regressions	In all three political stability groups, both moderate and severe food insecurity are negatively associated with life evaluation score. The coefficient for moderate food insecurity is smallest (in absolute terms), for those from low political stability countries, and greatest for those in medium political stability countries. Conversely, the estimated coefficient for severe food insecurity is largest (in absolute terms) in low political stability countries, and smallest in medium political stability countries. Both moderate and severe food insecurity are again found to have significant negative coefficients across all three political stability groups,	N/A

						with the estimated coefficients are much more similar than in the life evaluation model.	
Hadley *et al.* (2012)	Ethiopia (Jimma Province)	20 households	N/A	N/A	Qualitative study using semi-structured interviews	The interviews reveal that food insecurity may have both a direct wellbeing impact through the stress it causes, and may also indirectly influence wellbeing through reducing the ability of households to participate in cultural events. Participants worried about how they would be perceived by their neighbours and children when they could not provide enough food to eat.	Households revealed they utilised multiple coping strategies to try and alleviate the impact of food price rises. Food-based coping strategies included reduced dietary diversity, and fasting or going hungry. Non-food based strategies included using savings, selling clothes or other assets, and borrowing from friends or neighbours. Less commonly used coping strategies included sending children to live with others, begging, and relying on remittances from grown children.
Trudell *et al.* (2021)	African Countries	64 studies	Mental health measures	Numerous	Systematic review of the literature	57 of 58 quantitative studies found negative relationship between food insecurity and mental health outcomes. Papers which examined different severity of food insecurity found a dose-responsive relationship between food insecurity and mental health. Women and the elderly may be more susceptible to mental health impacts of food insecurity. Social support often found to be a protective factor.	N/A

Table A4: Summary of Literature on the Relationship between Conflict, Subjective Wellbeing, and Other Welfare Measures

Author(s)	Country	Data	Outcome Measure	Conflict Measure	Methods	Key Findings
Welsch (2008)	21 countries involved in civil conflict across Africa, South America, Asia, and Europe	Upsala Conflict Database and World Database of Happiness (both from year 2000)	SWB: Happiness on a four-point scale	Number of civil war related deaths per capita, change in civil war related deaths per capita	Macro-level approach where average national SWB is used as outcome in a linear multivariate regression	Number of deaths per capita significantly negatively associated with average SWB. Change in deaths exhibits stronger negative relationship with average SWB. Both number of and change in deaths appear to have both an indirect and direct impact on national SWB.
Shemyakina and Plagnol (2013)	Bosnia-Herzegovina	Observations on 9,400 individuals from the 2002 to 2004 waves of the Living in Bosnia and Herzegovina (Panel) Survey. Additional data from Bosnia Book of Dead Project (1991-1995)	SWB: Life satisfaction on 7-point scale	Two individual-level measures: binary variable for dwelling war damage, and weekly frequency of recollection of painful war memories (war trauma). Municipality-level measure of number of casualties per capita.	Repeated cross-section and panel multivariate regressions	Repeated cross-section: War damage negatively associated with life satisfaction in 2002 wave only. War trauma negatively associated with life satisfaction in 2003 and 2004 waves (not available in 2002). Municipality-level conflict not significantly associated with life satisfaction. Panel: War trauma significantly negatively associated with life satisfaction but with smaller coefficient than in repeated cross-section. Life satisfaction declined in 2004 relative to 2002 in municipalities with higher casualty rate (but authors note this may be due to municipality-level economic conditions).

Wills-Herrera *et al.* (2011)	Columbia (5 geographical regions)	742 observations on owners or managers of productive properties (collected by authors)	SWB: Satisfaction with: life as a whole, being part of a community, personal achievements, and political or religious beliefs	Individual-level: perceptions of insecurity measured across four domains: personal safety (PERINS), political freedom of voice and expressions (POLINS), economic security (ECOINS), security provided by the community (COMINS). Municipality-level: objective insecurity index reflecting number of homicides, kidnappings, armed clashes, and displaced people per 100,000	Individual- and multi-level regressions.	POLINS, ECOINS, and COMINS significantly negatively associated with SWB. Higher social capital increases wellbeing of those with low perceptions of insecurity even more. The objective insecurity index is not significantly associated with SWB.

				inhabitants in past 5 years.		
Bozzoli *et al.* (2011)	Uganda	3,600 households from the 2007 Northern Uganda Livelihood Survey. Supplemented with data from the Armed Conflict Location and Event Data (ACLED) in 2002 and 2006.	Other Welfare Measure(s): Binary variable equal to 1 if individual believes their economic situation will improve in the future, binary variables equal to 1 if individual believes their life will be "better than now" in one year's time.	Conflict intensity index constructed for 2002 and 2006	Cross-sectional multivariate linear regression	CII for 2002 weakly positively associated with future economic expectations, CII for 2006 strongly negatively associated with future economic expectations. 2002 CII negatively associated with general life expectations, 2006 CII not significant.
Dabalen and Paul (2014)	Ivory Coast	Observations on 10,800 households from 2002 round of the Ivory Coast's Household Living Standards Survey (HLSS) and on 12,600 from the 2008 round of the HLSS	Other Welfare Measure(s): Dietary diversity measured via the food consumption score (FCS) developed by the World Food Programme. Thresholds represent food security status	Various measures examined either based on comparison of pre-war (2002) and post-war data (2008), or dummy variable for experience of at least one conflict event at department	Difference-in-difference (DID) comparison of means and regression based DID (comparison of pre-war and post-war samples divided into conflict-heavy North and less-affected South). 2008 sample used with FCS regressed on	FCS scores lower in North pre-war, with scores falling in both North and South post-war but greater decline in conflict-affected North. Conflict dummy not significantly associated with FCS in whole sample. Significant negative coefficient found in sub-sample of departments which received food aid, non-significant coefficient in sub-sample of

		(repeated cross-section). Supplemented with data from the ACLED Project.	of household, with >35 acceptable, 21.5-35 borderline food insecure, and <21.5 food insecure.	level between 2002 to 2006 (obtained from ACLED). Nine self-reported impacts of conflict in 2008 wave.	ACLED-based conflict variable.	departments which did not receive food aid. Households who reported the conflict led to a registered death in their family, a fall in income, lost ownership of household property, loss of a job, or loss of a farm exhibited significantly lower FCS scores.

Table A5: Summary of Literature on the Relationship between Shocks and Mental Health

Author(s)	Country	Data	Mental Health Outcome	Self-Reported Shock(s)	Methods	Shock Findings	Other Findings
Hamad *et al.* (2008)	South Africa (Cape Town, Port Elizabeth, Durban)	Cross-section of 257 individuals (collected in 2004)	CES-D 20 Item Scale – total score (higher score indicates more depressive symptoms) Cohen's Perceived Stress Scale – total score (higher score indicates more perceived stress)	'Birth', 'Catastrophe' (fire or floods), 'Other' (weddings, funerals, theft, and initiation ceremonies)	OLS regression	Birth, catastrophe, and other shocks positively associated with depressive symptoms. Birth and catastrophe positively associated with greater perceived stress.	Number of people in household and being female positively associated with depressive symptoms in some specifications, being White rather than African ethnicity, education, perceived SES status, and having joint decision-making in household negatively associated with depressive symptoms in some specifications. Number of people in household, being female, being Multiracial rather than African ethnicity positively associated with perceived stress in some specifications, perceived SES status and creditworthiness negatively associated with perceived stress in some specifications.
Dowdall *et al.* (2017)	South Africa	Cross-section from NIDS on 11,995 individuals (2008 wave)	CES-D 10 Scale - total score (higher score indicates more	Binary variable for experiencing at least one of 12 shocks in past year.	OLS regressions	Experience of negative events not significantly associated with CES-D 10 score. Interaction between experience of negative events and income and	SAIMD Composite Index, SAIMD Income and Material, Employment, and Living Environment domains positively associated with depressive symptoms. Living with partner, widowed, divorced, never married

			depressive symptoms)			employment domains of SAIMD is negative	positively associated with depressive symptoms relative to being married, as are age, living in an urban area, and strict unemployment. Being White or Coloured relative to African negatively associated with depressive symptoms, as is household income, ownership of durable goods, and education.
Alloush (2018)	South Africa	Balanced panel of 6,975 individuals from the NIDS (four waves from 2008 to 2014)	CES-D 10 Scale - total score (higher score indicates more depressive symptoms)	Negative income and CES-D 10 shocks captured through error terms in two-equation system of individual income and CES-D 10 score	Structural VAR used to estimate Wold decomposition of the two-equation system	Impulse response functions for income and CES-D 10 score show that relative to a model whereby income and CES-D 10 score follow AR(1) processes, the impact of a negative income or depression shock on future incomes and future CES-D 10 scores are accentuated by the bi-directional relationship estimated in the sample. The total impact of these shocks also increases over time.	None.

Table A6: Summary of Literature on the Relationship between Shocks and Economic Welfare Outcomes

Author(s)	Country	Data	Welfare Outcome(s)	Observed Covariate Shock(s)	Self-reported Shock(s)	Coping Strategies	Methods	Key Finding(s)
Alloush (2018)	South Africa	Balanced panel of 6,975 individuals from the NIDS (four waves from 2008 to 2014)	Poverty Rates	N/A	Generated income and CES-D 10 score shocks	N/A	Simulation based on NIDS data	20% shock to income a time 0 leads to poverty rates which are approximately 20% higher for individuals who start simulation with CES-D 10 score of 9 or more by period 5.
Harrower and Hoddinott (2004)	Mali (Zone Lacustre)	Panel of 275 households (4 waves from 1997 to 1998)	Consumption	Unspecified village-time shocks captured by single dummy variable	Labour time lost to illness, theft or death of livestock, crop disease, inability to cultivate all available land	Migration, remittances, livestock sales, debt, gifts from family and friends. Partial consumption insurance at village level.	Fixed effects linear regression	Dummy variable capturing unspecified covariate shocks is highly significant. No self-reported shocks are significantly associated with consumption. Asset-poor households are more likely to use remittances, outmigration, gifts, and risk-pooling. Asset-nonpoor more likely to use debt and income diversification.
Dercon and Krishnan (2000)	Rural Ethiopia	Panel of 1,450 households (3 waves from 1994 to 1995)	Consumption	Rainfall deviations from long-term mean	Self-perceived rainfall variation, crop shock, livestock shock, labour time lost to illness	N/A	Fixed effects linear regression	Below average rainfall negatively associated with consumption. Livestock disease and crop shock negatively associated with consumption.

Porter (2012)	Rural Ethiopia	EHRS Panel 1,477 household (5 waves from 1994 to 2004)	Consumption	Rainfall quintiles in sample	Self-perceived rainfall variation, crop disease, illness in family, and death in household	Income diversification	OLS, random effects, fixed effects, and GMM regressions	Rainfall in bottom quintile negatively associated with consumption. No idiosyncratic shocks significantly associated with consumption. Rainfall and crop shocks negatively associated with crop income and positively associated with non-farm income.
Bene *et al.* (2012)	Ethiopia	'Trends and Transfer' Panel of 960 households (2006 and 2008 waves)	Food security and economic wellbeing	N/A	Drought, flooding, crop loss, livestock loss, high agricultural input prices, low output prices, illness of household members, other idiosyncratic shocks (death of household member, disability, theft, family split)	PSNP Social Protection programme. Reduce food consumption, sale of assets to buy food, reduce non-food spending, sale of livestock for food, sale of livestock for non-food, removal of children from school, child labour, sending children to live with other family	PSM comparison of means, probit regression	PSNP beneficiaries generally exhibit non-significant higher mean food security and economic wellbeing than non-PSNP beneficiaries. Shock-affected PSNP and non-PSNP households generally exhibit lower food security and economic wellbeing. PSNP beneficiaries protected against some idiosyncratic shocks, but have lower food security when experiencing drought or higher input prices, and lower economic wellbeing when experiencing drought,

								illness, and other idiosyncratic shocks.
Alem and Soderbom (2012)	Urban Ethiopia	EUSS Panel of 709 households (three waves from 2000 to 2008)	Food consumption Self-perceived impact of food price inflation Reduction of food consumption and/or eating less preferred foods	Food price inflation	Death of family member, job loss of family member, asset loss, other shock	N/A	Fixed effects on pooled data with shock period dummy. OLS and Probit on 2008 wave.	Food consumption (self-perceived impact) fell (increased) significantly for public sector and casual workers, and households headed by women in shock period. Household assets positively (negatively) associated with food consumption (self-perceived impact) in shock period. Only job loss negatively associated with food consumption.
d'Errico *et al.* (2018)	Tanzania and Uganda	TZNPS Panel of 2,866 households (three waves from 2008 to 2012). UHNS Panel of 2,031 households (three waves from 2009 to 2011/12)	Food security (daily caloric intake, Simpsons dietary diversity index).	Rainfall deviations from long-term average. Flood and drought.	Self-reported agricultural, climatic, labour market, health, and crime shocks.	Resilience Capacity Index.	Probit	Excessive rainfall and flooding associated with reduced daily caloric intake and dietary diversity. No idiosyncratic shocks significantly associated with food security outcomes. High resilience associated with lower probability of food insecurity and higher probability of recovery from food insecurity in next wave. High RCI also negates association between flooding and food insecurity.

Akter and Basher (2014)	Rural Bangladesh	Panel of 1,810 households (two waves from 2006/07 and 2009/10)	Food security and household expenditure	None	Positive shocks: level of remittances received, growth in remittance income, new receipt of government transfer. Negative shocks: Self-reported food shortages, ceased receipts of government transfer, flood and non-flood damages, unforeseen medical expenditure	N/A	Multinomial logitstic regression on 2009/10 wave. First-difference OLS regression on panel.	Losses and damages associated with negative shocks positively associated with reporting food shortage in a given year. Increase remittances associated with lower probability of reporting food shortage in a given year. Asset-poor households more likely to report food shortages. Food shortages in 2007 associated with reduced household expenditure in 2009/10, positive transfer shock and remittance growth positively associated with household expenditure in 2009/10. No other negative income shocks significant.
Skoufias (2003)	Russia	RLMS Panel of 14,097 observations on households (five waves from 1994 to 2000)	Total consumption, food consumption, non-food consumption	None	Between wave incidence of job loss, wage arrears, and forced leave from job.	Getting a second job, informal labour market activities, receipt of transfers, borrowing, sale of assets, sale of poultry, current land cultivation, land cultivation in last year.	OLS and Probit	Incidence of wage arrears and unemployment negatively associated with total consumption. Job loss negatively associated with food and non-food consumption. Wage arrears negatively associated with non-food consumption. Results only hold for urban households.

						Community-level partial insurance.		No strategies vary by shock-type: Wage arrears positively associated with borrowing; Forced leave positively associated with getting a second job; Unemployment negatively associated with getting a second job and informal labour market activities, positively associated with receiving transfers, and selling assets. Some evidence of community-level risk pooling

Appendix 1B: Description of Variables

Table B1: Description of Variables

Variable	Type	Level	Description	Expected Direction of Coefficient
Dependent Variable				
Life Satisfaction	Ordinal	Individual	How satisfied or dissatisfied the individual is with their life as a whole: = 1 if "Very Dissatisfied" = 2 if "Dissatisfied" = 3 if "Somewhat Dissatisfied" = 4 if "Neither Satisfied nor Dissatisfied" = 5 if "Somewhat Satisfied" = 6 if "Satisfied" = 7 if "Very Satisfied"	N/A
Household Shocks				
Large Rise in the Price of Food	Binary	Household	= 1 if household stated a "large rise in the price of food" was one of the three most severe shocks they experienced in the last 2 years = 0 otherwise	Negative
Labour Market Shock	Binary	Household	Note: this variable combines two household shocks = 1 if household stated a "loss of salaried employment or non-payment of salary" and/or "household business failure" were on of the three most severe shocks they experienced in the last 2 years = 0 otherwise	Negative
Chronic or Severe Illness or Accident of Household Member	Binary	Household	= 1 if household stated "chronic/severe illness or accident of household member" was one of the three most severe shocks they experienced in the last 2 years = 0 otherwise	Negative

Death of Household Member	Binary	Household	= 1 if household stated "death of a household member" was one of the three most severe shocks they experienced in the last 2 years = 0 otherwise	Negative
Death of Other Member of Family	Binary	Household	= 1 if household stated "death of other family member" was one of the three most severe shocks they experienced in the last 2 years = 0 otherwise	Negative
Hijacking, Burglary or Assault	Binary	Household	= 1 if household stated "hijacking/burglary/assault" was one of the three most severe shocks they experienced in the last 2 years = 0 otherwise	Negative
Break-Up of Household	Binary	Household	= 1 if household stated "Break-up of the household" was one of the three most severe shocks they experienced in the last 2 years = 0 otherwise	Negative
Other Idiosyncratic Shock	Binary	Household	Note: this variable combines three household shocks = 1 if household stated "dwelling damaged or destroyed" and/or "fire" and/or "jailed" were one of the three most severe shocks they experienced in the last 2 years = 0 otherwise	Negative
Other Unspecified Shock	Binary	Household	= 1 if household stated another shock not included in the questionnaire was one of the three most severe shocks they experienced in the last 2 years = 0 otherwise	Negative
Food Insecurity Variables				
Food Insecure	Binary	Household	= 1 if household head answered 'yes' to "in the last 12 months, have you been faced with a situation when you did not have enough food to feed the household?" = 0 otherwise	Negative

Food to Total Expenditure Ratio	Continuous	Household	Total household food consumption divided by total household consumption	Negative
Conflict Variables				
Conflict Intensity Index	Continuous	Household	Utilises data from the Armed Conflict and Events Data (ACLED) Project (ref.) in conjunction with the TZNPS. Constructed using the methodology of Bozzoli *et al.* (2011). Conflict Intensity Index (CII) for a household in a given year is: $\sum_{j=1}^{J} e^{-\alpha(d(c_j,i))}$ Where α is the distance discount factor (set to 10 as in original authors' paper), and $d(c_j, i) = \parallel c_j - i \parallel^2$ is the estimated distance in degrees between conflict event c_j and household *i*. Note: Not included in regression	N/A
Change in Conflict Intensity Index	Continuous	Household	The change in the conflict intensity index from year prior to interview to year of interview (not from wave 2 to wave 3)	Negative
Control Variables				
Real Total Household Consumption (TSH)	Continuous	Household	Total annual real household consumption in Tanzanian Shillings (TSh). This is calculated by the authors of the TZNPS, with further details available in 'Appendix C: Consumption Aggregate' in the 'Basic Information Document' (can be accessed via https://microdata.worldbank.org/index.php/catalog/1050/related-materials) Note: Not included in regression	N/A
Real Total Household Consumption Per Adult Equivalent	Continuous	Household	Total annual real household consumption in TSh per adult equivalent Note: Not included in regression	N/A
Log of Real Total Household Consumption	Continuous	Household	Natural logarithm of real total household consumption per adult equivalent	Positive

Per Adult Equivalent				
Age	Continuous	Individual	Age of individual in years	Negative
Age Squared	Continuous	Individual	Square of age of individual in years	Positive
Education Level: None	Binary	Individual	= 1 if individual has never been to school = 0 otherwise Note: Omitted as reference case	N/A
Education: Primary School	Binary	Individual	= 1 if individual's highest level of education is primary school = 0 otherwise	Positive
Education: High School or Abovex	Binary	Individual	= 1 if individual's highest level of education is secondary school or university = 0 otherwise	Positive
Male	Binary	Individual	= 1 if individual is male = 0 otherwise	Positive
Marital Status: Monogamously Married	Binary	Individual	= 1 if individual is monogamously married = 0 otherwise Note: Omitted as reference case	N/A
Marital Status: Polygamously Married	Binary	Individual	= 1 if individual is polygamously married = 0 otherwise	Not Significant
Marital Status: Lives with Partner	Binary	Individual	= 1 if individual lives with their partner, but is not married to them = 0 otherwise	Not Significant
Marital Status: Separated or Divorced	Binary	Individual	= 1 if individual is separated or divorced = 0 otherwise	Negative

Marital Status: Never Married	Binary	Individual	= 1 if individual has never been married (and is not living with a partner) = 0 otherwise	Negative
Marital Status: Widow(er)	Binary	Individual	= 1 if individual is a widow(er) = 0 otherwise	Negative
Household Size Adult Equivalent	Continuous	Household	Number of adult equivalent household members. This is calculated by the authors of the TZNPS, with further details available in 'Appendix C: Consumption Aggregate' in the 'Basic Information Document' (can be accessed via https://microdata.worldbank.org/index.php/catalog/1050/related-materials) Note: Not used in the regression, but needed for the real household consumption per adult equivalent calculation	N/A
Overnight Stay in Healthcare Facility in Past Year	Binary	Individual	= 1 if individual has stayed at least one night in a hospital or traditional healer's or faith healer's dwelling in the last 12 months = 0 otherwise	Negative
Borrowed in Last 12 Months	Binary	Household	=1 if the household has borrowed cash, goods, or services from someone outside of the household or from an institution in the past 12 months = 0 otherwise	Negative
Health Satisfaction	Ordinal	Individual	How satisfied or dissatisfied the individual is with their health = 1 if "Very dissatisfied" = 2 if "Dissatisfied" = 3 if "Somewhat dissatisfied" = 4 if "Neither satisfied nor dissatisfied" = 5 if "Somewhat satisfied" = 6 if "Satisfied" = 7 if "Very satisfied"	N/A

			Note: Health satisfaction is included as a series of binary variables for each response in the regression	
Health Satisfaction: "Very Dissatisfied"	Binary	Individual	= 1 if individual is "very dissatisfied" with their health = 0 otherwise Note: Omitted as reference case	N/A
Health Satisfaction: "Dissatisfied"	Binary	Individual	= 1 if individual is "dissatisfied" with their health = 0 otherwise	Positive
Health Satisfaction: "Somewhat Dissatisfied"	Binary	Individual	= 1 if individual is "somewhat dissatisfied" with their health = 0 otherwise	Positive
Health Satisfaction: "Neither Satisfied nor Dissatisfied"	Binary	Individual	= 1 if individual is "neither satisfied or dissatisfied" with their health = 0 otherwise	Positive
Health Satisfaction: "Somewhat Satisfied"	Binary	Individual	= 1 if individual is "somewhat satisfied" with their health = 0 otherwise	Positive
Health Satisfaction: "Satisfied"	Binary	Individual	= 1 if individual is "satisfied" with their health = 0 otherwise	Positive
Health Satisfaction: "Very Satisfied"	Binary	Individual	= 1 if individual is "very satisfied" with their health = 0 otherwise	Positive
Financial Satisfaction	Ordinal	Individual	How satisfied or dissatisfied the individual is with their financial situation = 1 if "Very dissatisfied" = 2 if "Dissatisfied" = 3 if "Somewhat dissatisfied" = 4 if "Neither satisfied nor dissatisfied"	N/A

			= 5 if "Somewhat satisfied" = 6 if "Satisfied" = 7 if "Very satisfied" Note: Financial satisfaction is included as a series of binary variables for each response in the regression	
Financial Satisfaction: "Very Dissatisfied"	Binary	Individual	= 1 if individual is "very dissatisfied" with their financial situation = 0 otherwise Note: Omitted as reference case	N/A
Financial Satisfaction: "Dissatisfied"	Binary	Individual	= 1 if individual is "dissatisfied" with their health = 0 otherwise	Positive
Financial Satisfaction: "Somewhat Dissatisfied"	Binary	Individual	= 1 if individual is "somewhat dissatisfied" with their financial situation = 0 otherwise	Positive
Financial Satisfaction: "Neither Satisfied nor Dissatisfied"	Binary	Individual	= 1 if individual is "neither satisfied or dissatisfied" with their financial situation = 0 otherwise	Positive
Financial Satisfaction: "Somewhat Satisfied"	Binary	Individual	= 1 if individual is "somewhat satisfied" with their financial situation = 0 otherwise	Positive
Financial Satisfaction: "Satisfied"	Binary	Individual	= 1 if individual is "satisfied" with their financial situation = 0 otherwise	Positive
Financial Satisfaction: "Very Satisfied"	Binary	Individual	= 1 if individual is "very satisfied" with their financial situation = 0 otherwise	Positive
Housing Satisfaction	Ordinal	Individual	How satisfied or dissatisfied the individual is with their housing = 1 if "Very dissatisfied"	N/A

			= 2 if "Dissatisfied" = 3 if "Somewhat dissatisfied" = 4 if "Neither satisfied nor dissatisfied" = 5 if "Somewhat satisfied" = 6 if "Satisfied" = 7 if "Very satisfied" Note: Housing satisfaction is included as a series of binary variables for each response in the regression	
Housing Satisfaction: "Very Dissatisfied"	Binary	Individual	= 1 if individual is "very dissatisfied" with their housing = 0 otherwise Note: Omitted as reference case	N/A
Housing Satisfaction: "Dissatisfied"	Binary	Individual	= 1 if individual is "dissatisfied" with their housing = 0 otherwise	Positive
Housing Satisfaction: "Somewhat Dissatisfied"	Binary	Individual	= 1 if individual is "somewhat dissatisfied" with their housing = 0 otherwise	Positive
Housing Satisfaction: "Neither Satisfied or Dissatisfied"	Binary	Individual	= 1 if individual is "neither satisfied or dissatisfied" with their housing = 0 otherwise	Positive
Housing Satisfaction: "Somewhat Satisfied"	Binary	Individual	= 1 if individual is "somewhat satisfied" with their housing = 0 otherwise	Positive
Housing Satisfaction: "Satisfied"	Binary	Individual	= 1 if individual is "satisfied" with their housing = 0 otherwise	Positive
Housing Satisfaction: "Very Satisfied"	Binary	Individual	= 1 if individual is "very satisfied" with their housing = 0 otherwise	Positive

Occupation: Agriculture, Livestock or Fishing	Binary	Individual	= 1 if individual is employed in agriculture, livestock, or fishing = 0 otherwise	Positive
Occupation: Family Worker	Binary	Individual	= 1 if individual is a family worker (either paid or unpaid) = 0 otherwise	Positive
Occupation: Other Employment	Binary	Individual	= 1 if individual is employed in private enterprise, a government worker, self-employed, or undertakes mining or tourism, parastatal, or NGO or religious work = 0 otherwise	Positive
Occupation: Student	Binary	Individual	= 1 if individual is a student = 0 otherwise	Positive
Occupation: Not Working	Binary	Individual	= 1 if individual has no job, is job seeking, or disabled = 0 otherwise Note: Omitted as reference case	N/A
Household Occupational Diversity	Continuous	Household	The number of individuals in the household employed in paid jobs in different areas (*i.e.*, agriculture, livestock, fishing, paid family worker, private enterprise, government, self-employed, mining, tourism, parastatal, NGO, or religious work)	Positive
Household Asset Index	Continuous	Household	Total number of the following household goods owned: Radio and Radio Cassette; Telephone (landline); Telephone (mobile); Television; Video/DVD; Computer; Record/cassette player, tape recorder; Complete music system; Dish antenna/decoder; Fan or aircon; Motor vehicles; Motorcycles; Chairs; Sofas; Tables; Beds; Cupboards; Chest-of-drawers; Boxes; Wardrobes; Bookcases; Lanterns; Cooking pots; Cups; Other kitchen utensils; Mosquito nets; Books (not school books); Bicycles; Iron (charcoal or electric); Sewing machines; Watches; Other stoves; Fridge or freezer; Electric or gas stove; Water-heater	Positive
Agricultural Asset Index	Continuous	Household	Total number of the following agricultural machines owned by the household: Spraying machine; Water pumping set; Tractor; Milking	Positive

			machine; Harvesting and threshing machine; Hand milling machine; Coffee pulping machine; Fertiliser distributor; Outboard engine; Boat/Canoe; Carts; Animal-drawn cart; Wheelbarrow; Hoes; Reapers; Trailer for tractors; Plough; Harrow	
Animal Asset Index	Continuous	Household	Total number of the following animals owned by the household: Livestock; Poultry; Donkeys	Positive
Received Assistance from the Gov't or NGO in Last 12 Months	Binary	Household	= 1 if household received any of the following assistance from the government or an NGO in the past 12 months: Free food/maize distribution; Food-for-work or cash-for-work programme; Inputs-for-work programme; Scholarships or bursaries for primary school; Scholarships or bursaries for secondary school; Any other unlisted assistance. = 0 otherwise	Positive
Access to Electricity	Binary	Household	= 1 if household uses electricity for lighting = 0 otherwise	Positive
Access to Sanitary Toilet Facilities	Binary	Household	= 1 if household has access to sanitary toilet facilities (flush, pit latrine, VIP, washable slab, pour flush) = 0 otherwise	Positive
Area: Dar es Salaam	Binary	Household	= 1 if individual lives in Dar es Salaam = 0 otherwise Note: Omitted as reference case	N/A
Area: Rest of Urban	Binary	Household	= 1 if individual lives in rest of urban = 0 otherwise	Negative
Area: Rural	Binary	Household	= 1 if individual lives in a rural area = 0 otherwise	Positive
Area: Zanzibar	Binary	Household	= 1 if individual lives in a rural area = 0 otherwise	Positive
Wave 2	Binary	Individual	= 1 if individual is present in wave 2	N/A

			= 0 otherwise Note: Omitted as reference	
Wave 3	Binary	Individual	= 1 if individual is present in wave 3 = 0 otherwise	N/A
Region	Binary	Regional	Series of binary controls for the region in which the household is located: Arusha, Kilimanjaro, Tanga, Morogoro, Pwani, Dar es Salaam, Lindi, Mtwara, Ruvuma, Iringa, Mbeya, Singida, Tabora, Rukwa, Kigoma, Shinyanga, Kagera, Mwanza, Mara, Manyara, Kaskazini Unguja, Kusini Unguja, Mjini/Magharibi Unguja, Kaskazini Pemba, Kusini Pemba (omitted)	N/A
Note: Expected direction for the coefficients were based on findings from the existing literature, summarised in Tables A1-A6, where possible.				

Appendix 1C: Conflict Events in the ACLED

Table C1: Overview of Conflict Event Types from the ACLED Data

Year	Total Events	Battles	Explosions or Remote Violence	Protests	Riots	Strategic Developments	Violence Against Civilians	Mean CII
2009	9	0	0	2	3	0	4	0.275
2010	5	0	0	1	0	1	3	0.080
2011	49	9	0	13	10	3	14	0.683
2012	91	2	1	28	27	6	27	2.467
2013	74	5	3	12	28	5	21	1.448

Appendix 1D: Full Results Tables

Table D1: Full Results of the Life Satisfaction Linear Fixed Effects Regression

Variable	(1) Coefficient (t-stat)
Large Rise in the Price of Food	-0.028 (-0.60)
Labour Market Shock	-0.048 (-0.38)
Chronic or Severe Illness or Accident of Household Member	-0.280** (-2.36)
Death of Household Member	0.063 (0.72)
Death of Other Member of Family	-0.094* (-1.81)
Hijacking, Burglary or Assault	-0.072 (-0.70)
Break-Up of Household	-0.154 (-1.30)
Other Idiosyncratic Shock	-0.598*** (-3.60)
Other Unspecified Shock	0.087 (0.51)
Change in Conflict Intensity Index (Between Year of Interview and Year Prior to Interview)	-0.013* (-1.78)
Log of Real Household Consumption	0.092* (1.78)
Food to Total Expenditure Ratio	-0.323* (-1.74)
Food Insecure	-0.097** (-1.96)
Age	0.087 0.86
Age Squared	0.001 (1.09)
Education Level: Primary School	-0.346*** (-3.03)
Education Level: High School or Above	-0.028 (-0.14)
Marital Status: Polygamously Married	0.170 (1.51)
Marital Status: Lives with Partner	0.028 (0.37)
Marital Status: Separated or Divorced	-0.071 (-0.61)
Marital Status: Never Married	-0.142 (-1.06)
Marital Status: Widow(er)	-0.003 (-0.02)
Occupational Status: Employed in Agriculture, Livestock, or Fishery	0.036 (0.24)
Occupation Status: Family Employment	0.104 (0.75)

Occupational Status: Employed in Non-Agricultural Sector	0.096 (0.60)
Occupational Status: Student	-0.327 (-0.67)
Household Occupational Diversity	0.027 (0.49)
Borrowed in Last 12 Months	0.000 (0.00)
Household Asset Index	0.000 (0.53)
Animal Asset Index	0.001 (0.54)
Agricultural Asset index	-0.015 (-1.39)
Overnight Stay in Healthcare Facility in Last 12 Months	-0.111 (-1.48)
Health Satisfaction: "Dissatisfied"	-0.162 (-1.29)
Health Satisfaction: "Somewhat Dissatisfied"	-0.162 (-1.05)
Health Satisfaction: "Neither Satisfied nor Dissatisfied"	-0.146 (-0.74)
Health Satisfaction: "Somewhat Satisfied"	0.021 (0.17)
Health Satisfaction: "Satisfied"	-0.046 (-0.38)
Health Satisfaction: "Very Satisfied"	-0.257** (-2.15)
Financial Satisfaction: "Dissatisfied"	0.510*** (8.01)
Financial Satisfaction: "Somewhat Dissatisfied"	0.848*** (8.48)
Financial Satisfaction: "Neither Satisfied nor Dissatisfied"	1.257*** (9.41)
Financial Satisfaction: "Somewhat Satisfied"	1.504*** (19.40)
Financial Satisfaction: "Satisfied"	1.880*** (22.76)
Financial Satisfaction: "Very Satisfied"	2.685*** (19.62)
Housing Satisfaction: "Dissatisfied"	0.109 (1.23)
Housing Satisfaction: "Somewhat Dissatisfied"	0.419*** (3.33)
Housing Satisfaction: "Neither Satisfied nor Dissatisfied"	0.317* (1.92)
Housing Satisfaction: "Somewhat Satisfied"	0.628*** (6.98)
Housing Satisfaction: "Satisfied"	0.917*** (10.42)
Housing Satisfaction: "Very Satisfied"	1.160*** (11.09)
Received Assistance from the Gov't or NGO in Last 12 Months	0.192*** (3.68)

Household Access to Toilet Facilities	0.126 (1.43)
Household has Electricity	0.159 (1.40)
Area: Rest of Urban	1.365* (1.91)
Area: Rural	1.741** (2.49)
Area: Zanzibar	0.611 (0.34)
Wave 3	-0.394** (-2.14)
Regional Controls	Yes
N	17,461

Notes: Model estimated using linear regression with fixed effects. Additional control variables, including time and region dummies, are included but not reported for brevity. Coefficients are reported to 3 decimal places. T-statistics are reported to 2 decimal places and are in parentheses. Statistical significance indicated by * at the 10% level, ** at the 5% level, and *** at the 1% level.

Appendix 2: Chapter Three

Appendix 2A: NIDS-CRAM Data Collection and Timing of COVID-19 Restrictions

Table A1: NIDS-CRAM Data Collection and Timing of COVID-19 Restrictions

NIDS-CRAM Wave	Data Collection Dates[1]	Frequency of Depressive Feelings	Alert Level[2]	Tobacco Sales Ban
1	7 May to 27 June 2020	No	4 (From 1 to 31 May 2020) 3 (From 1 June to 17 August 2020)	Yes
2	13 July to 13 August 2020	Yes	3 (From 1 June to 17 August 2020)	Yes
3	2 November to 13 December 2020	Yes	1 (From 21 September to 28 December 2020)	No
4	2 February to 10 March 2021	No	3 (From 29 December 2020 to 28 February 2021) 1 (From 1 March to 30 May 2021)	No
5	6 April to 11 May 2021	Yes	1 (From 1 March to 30 May 2021)	No

Notes:
[1] NIDS-CRAM Wave 5 Panel User Manual (Ingle *et al.*, 2021)
[2] South African Government Website: https://www.gov.za/Coronavirus

Appendix 2B: Full Descriptive Statistics for Baseline Sample

Table B1. Full Descriptive Statistics for All Variables

Variable	Mean	S.D.	Minimum	Maximum
Dependent Variables				
Frequency of Depressive Feelings	0.627	0.833	0	3
Frequency of Depressive Feelings = 0	0.562	0.496	0	1
Frequency of Depressive Feelings = 1	0.289	0.453	0	1
Frequency of Depressive Feelings = 2	0.108	0.311	0	1
Frequency of Depressive Feelings = 3	0.041	0.197	0	1
Moderate-to-High Frequency of Depressive Feelings	0.149	0.356	0	1
Independent Variables				
Smoker	0.184	0.398	0	1
Continuer	0.005	0.069	0	1
Tobacco Sales Ban	0.045	0.208	0	1
Female	0.612	0.487	0	1
Race: Black African	0.828	0.377	0	1
Race: Coloured	0.132	0.338	0	1
Race: Asian/Indian	0.010	0.101	0	1
Race: White	0.030	0.170	0	1
Age	40.430	16.729	18	110
Employment Status: Not Economically Active	0.409	0.492	0	1
Employment Status: Unemployed	0.187	0.390	0	1
Employment Status: Employed	0.405	0.491	0	1
Highest Education: No Schooling	0.102	0.303	0	1
Highest Education: Primary	0.200	0.400	0	1
Highest Education: Grades 8-9	0.141	0.348	0	1
Highest Education: NQF 2-4	0.386	0.487	0	1
Highest Education: Tertiary	0.171	0.376	0	1
Marital Status: Married or Living with Partner	0.357	0.479	0	1
Real Total Monthly Household Income Per Capita	R1,268	R1,931	R35	R16,120
Log of Real Total Monthly Household Income Per Capita	R6.473	R1.127	R3.568	R9.688
Household Receipt of Government Grant	0.681	0.466	0	1
Geo-type: Traditional	0.404	0.491	0	1
Geo-type: Urban	0.533	0.499	0	1
Geo-type: Farm	0.064	0.244	0	1
Household Size	5.266	3.387	1	45

Variable	Mean	S.D.	Minimum	Maximum
Date and Regional Controls				
Interview Month: January	0.029	0.168	0	1
Interview Month: February	0.061	0.240	0	1
Interview Month: March	0.092	0.288	0	1
Interview Month: April	0.130	0.336	0	1
Interview Month: May	0.093	0.291	0	1
Interview Month: June	0.100	0.300	0	1
Interview Month: July	0.121	0.325	0	1
Interview Month: August	0.087	0.282	0	1
Interview Month: September	0.078	0.268	0	1
Interview Month: October	0.089	0.285	0	1
Interview Month: November	0.082	0.275	0	1
Interview Month: December	0.037	0.189	0	1
Wave 1	0.131	0.337	0	1
Wave 2	0.150	0.357	0	1
Wave 3	0.173	0.378	0	1
Wave 4	0.205	0.404	0	1
Wave 5	0.197	0.398	0	1
Wave 7 (Ban)	0.045	0.208	0	1
Wave 8	0.054	0.227	0	1
Wave 9	0.044	0.205	0	1
Province: Western Cape	0.109	0.312	0	1
Province: Eastern Cape	0.115	0.319	0	1
Province: Northern Cape	0.075	0.263	0	1
Province: Free State	0.062	0.242	0	1
Province: KwaZulu-Natal	0.278	0.448	0	1
Province: North West	0.065	0.247	0	1
Province: Gauteng	0.122	0.374	0	1
Province: Mpumalanga	0.078	0.268	0	1
Province: Limpopo	0.095	0.293	0	1

Notes: Statistics reflect the (unweighted) baseline sample (N=85,958) used for testing *H1*, *H2*, and *H3* with linear fixed effects estimation. Figures are correct to three decimal places, except for income which is rounded to the nearest whole number.

Appendix 2C: Tests of Parallel Trends Assumption

Table C1. Test of Parallel Trends Assumption with Unbalanced and Entropy Balanced Sample

Variable	(1) FDF	(2) FDF
	Coefficient (t-statistic)	Coefficient (t-statistic)
Smoker x Wave 2	0.008 (0.28)	0.027 (0.75)
Smoker x Wave 3	0.066** (2.35)	0.047 (1.31)
Smoker x Wave 4	0.050* (1.84)	0.018 (0.52)
Smoker x Wave 5	0.026 (0.92)	0.033 (0.95)
Smoker x Ban	0.097* (1.66)	0.079 (1.17)
Smoker x Wave 8	0.096* (1.74)	0.028 (0.42)
Smoker x Wave 10	0.023 (0.41)	-0.006 (-0.09)
Entropy Balanced	No	Yes
Controls	Yes	Yes
N	85,958	85,958

Notes: All figures correct to 3 decimal places. Statistical significance is indicated by * at the 10%, ** at the 5%, and *** at the 1% level. Individual, gender, race, month, wave, and provincial fixed effects absorbed through *reghdfe* command in Stata 17. Individual- and household-level controls includes but not reported (available on request).

Figure C1. Test of Parallel Trends Assumption with Unbalanced Sample

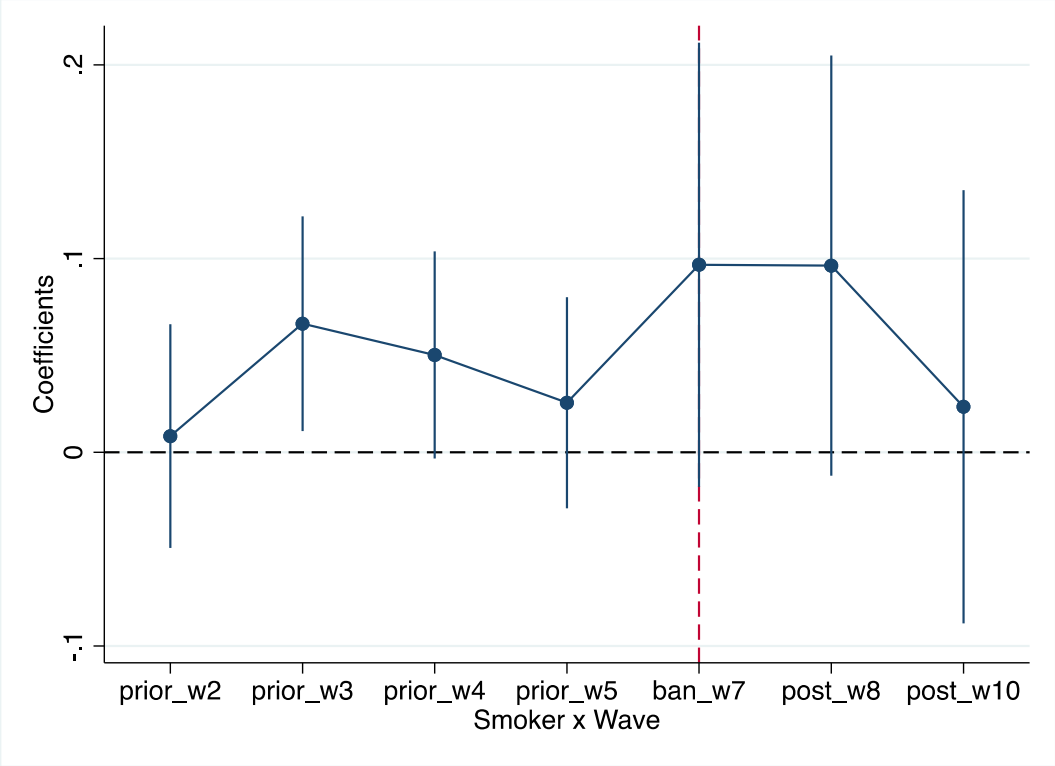
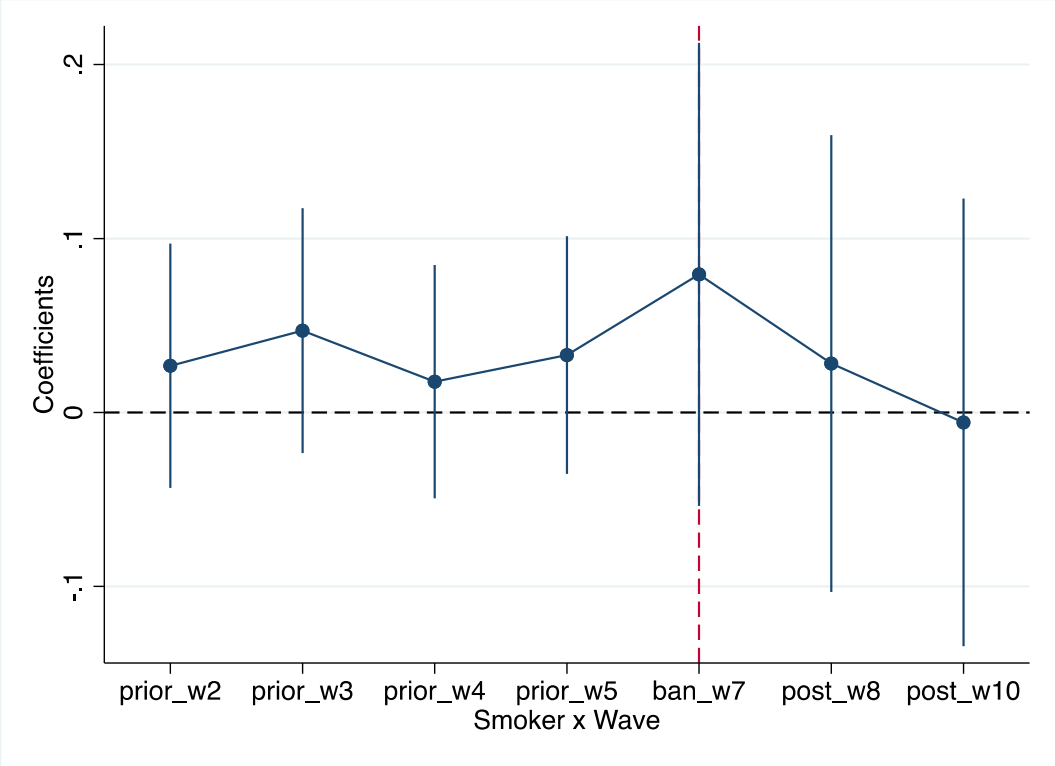


Figure C2. Test of Parallel Trends Assumption with Entropy Balanced Sample



Appendix 2D: Entropy Balancing Results

Table D1. Entropy Balancing Results on First and Second Moments of Selected Covariates between Smokers and Non-Smokers

Variable	Non-Smokers – Before Entropy Balancing N = 70,164		Non-Smokers – After Entropy Balancing N = 70,164		Smokers N = 15,794	
	Mean	Variance	Mean	Variance	Mean	Variance
Age	40.53	294.900	40.000	212.800	40.000	212.800
Employment Status: Unemployed	0.187	0.152	0.183	0.150	0.182	0.150
Employment Status: Employed	0.380	0.236	0.513	0.250	0.513	0.250
Highest Education: Primary	0.186	0.151	0.261	0.193	0.261	0.193
Highest Education: Grades 8-9	0.131	0.114	0.186	0.151	0.186	0.151
Highest Education: NQF 2-4	0.398	0.240	0.331	0.222	0.331	0.222
Highest Education: Tertiary Education	0.178	0.147	0.136	0.117	0.136	0.117
Married/Partner Living Together	0.347	0.227	0.398	0.240	0.398	0.240
Log of Real Household Income Per Capita	R6.444	1.288	R6.603	1.164	R6.604	1.164
Receipt of Government Grant	0.696	0.212	0.615	0.237	0.615	0.238
Geo Type: Urban	0.503	0.250	0.663	0.223	0.663	0.223
Geo Type: Farm	0.056	0.053	0.098	0.088	0.098	0.088
Household Size	5.381	11.760	6.603	9.842	4.752	9.842
Race: Coloured	0.089	0.081	0.320	0.218	0.320	0.218
Race: Asian/Indian	0.010	0.009	0.014	0.013	0.014	0.013
Race: White	0.026	0.026	0.045	0.043	0.045	0.043

Female	0.692	0.213	0.259	0.192	0.259	0.192
Province: Eastern Cape	0.116	0.103	0.110	0.098	0.110	0.098
Province: Northern Cape	0.061	0.057	0.134	0.116	0.134	0.116
Province: Free State	0.060	0.057	0.072	0.067	0.072	0.067
Province: KwaZulu-Natal	0.301	0.211	0.175	0.144	0.175	0.144
Province: North West	0.067	0.062	0.060	0.057	0.060	0.057
Province: Gauteng	0.122	0.107	0.122	0.107	0.122	0.107
Province: Mpumalanga	0.083	0.076	0.056	0.053	0.056	0.053
Province: Limpopo	0.105	0.094	0.051	0.049	0.051	0.049
Notes: All figures correct to three decimal places. Entropy balancing conducted with Stata user written package *ebalance* (Hainmueller and Xu, 2013).						

Appendix 2E: Full Results for Baseline Analysis

Table E1. Linear Fixed Effects Regression of Frequency of Depressive Feelings Testing *H2*

Variable	(1) FDF	(2) FDF
	Coefficient (t-statistic)	Coefficient (t-statistic)
Smoker	0.067*** (4.49)	0.065*** (3.81)
Ban	0.094 (1.01)	0.001 (0.01)
Smoker x Ban	-0.152 (-1.13)	-0.154 (-1.10)
Smoker x Ban x Continuer	0.237* (1.66)	0.243* (1.67)
Age	0.010 (1.21)	0.015 (1.17)
Age Squared	-0.000*** (-9.75)	-0.000*** (-4.75)
Employment Status: Unemployed	-0.022** (-2.12)	-0.012 (-0.70)
Employment Status: Employed	-0.051*** (-4.93)	-0.066*** (-3.87)
Highest Education: Primary	0.041 (1.10)	0.005 (0.08)
Highest Education: Grades 8-9	0.020 (0.45)	0.033 (0.44)
Highest Education: NQF 2-4	0.015 (0.33)	0.065 (0.85)
Highest Education: Tertiary Education	0.019 (0.40)	0.047 (0.62)
Married/Partner Living Together	-0.047*** (-3.63)	-0.049** (-2.40)
Log of Real Household Income Per Capita	-0.028*** (-5.11)	-0.045*** (-5.16)
Receipt of Government Grant	-0.018* (-1.92)	-0.026* (-1.73)
Geo Type: Urban	0.023 (1.27)	0.037 (1.25)
Geo Type: Farm	0.014 (0.48)	0.043 (0.99)
Household Size	-0.003 (-1.49)	-0.009*** (-3.07)
Entropy Balanced	No	Yes
N	85,958	85,958

Notes: All figures correct to 3 decimal places. Statistical significance is indicated by * at the 10%, ** at the 5%, and *** at the 1% level. Models estimated using linear fixed effects regression. Individual, gender, race, month, wave, and provincial fixed effects absorbed through *reghdfe* command in Stata 17.

Table E2. Linear Fixed Effects Regression of Frequency of Depressive Feelings Testing *H3*

Variable	(1) FDF	(2) FDF
	Coefficient (t-statistic)	Coefficient (t-statistic)
Smoker	0.073*** (4.27)	0.074*** (3.82)
Ban	0.138 (1.45)	0.009 (0.06)
Smoker x Female	-0.020 (-0.60)	-0.048 (-1.24)
Ban x Female	-0.068* (-1.94)	-0.041 (-0.80)
Smoker x Ban	-0.060 (-1.00)	-0.024 (-0.35)
Smoker x Ban x Female	0.397*** (3.02)	0.395*** (2.89)
Age	0.010 (1.24)	0.015 (1.22)
Age Squared	-0.000*** (-9.76)	-0.000*** (-4.82)
Employment Status: Unemployed	-0.022** (-2.12)	-0.012 (-0.71)
Employment Status: Employed	-0.051*** (-4.92)	-0.066*** (-3.89)
Highest Education: Primary	0.041 (1.09)	0.004 (0.07)
Highest Education: Grades 8-9	0.020 (0.44)	0.033 (0.43)
Highest Education: NQF 2-4	0.015 (0.32)	0.063 (0.83)
Highest Education: Tertiary Education	0.018 (0.39)	0.045 (0.59)
Married/Partner Living Together	-0.047*** (-3.64)	-0.048*** (-2.37)
Log of Real Household Income Per Capita	-0.028*** (-5.16)	-0.045*** (-5.17)
Receipt of Government Grant	-0.018* (-1.90)	-0.026* (-1.71)
Geo Type: Urban	0.023 (1.30)	0.038 (1.28)
Geo Type: Farm	0.015 (0.53)	0.046 (1.04)
Household Size	-0.003 (-1.49)	-0.009*** (-3.08)
Entropy Balanced	No	Yes
N	85,958	85,958

Notes: All figures correct to 3 decimal places. Statistical significance is indicated by * at the 10%, ** at the 5%, and *** at the 1% level. Models estimated using linear fixed effects regression. Individual, gender, race, month, wave, and provincial fixed effects absorbed through *reghdfe* command in Stata 17.

Appendix 2F: Full Results for Robustness Checks

Table F1. Robustness Check 1: Linear Probability Models for Moderate-to-High Frequency of Depressive Feelings

Panel A: Hypothesis 1		Panel B: Hypothesis 2		Panel C: Hypothesis 3	
Variable	(1) FDF ≥ 2	Variable	(2) FDF ≥ 2	Variable	(3) FDF ≥ 2
	Coefficient (t-statistic)		Coefficient (t-statistic)		Coefficient (t-statistic)
Smoker	0.017** (2.39)	Smoker	0.018** (2.41)	Smoker	0.020** (2.38)
Ban	0.041 (0.62)	Ban	0.041 (0.62)	Ban	0.047 (0.70)
Smoker x Ban	0.024 (1.03)	Smoker x Ban	-0.069 (-1.27)	Smoker x Ban	0.002 (0.07)
		Smoker x Ban x Continuer	0.107* (1.87)	Smoker x Female	-0.012 (-0.69)
				Ban x Female	-0.026 (-1.40)
				Smoker x Ban x Female	0.101* (1.83)
Age	0.003 (0.56)	Age	0.003 (0.57)	Age	0.003 (0.58)
Age Squared	-0.000*** (-3.51)	Age Squared	-0.000 (-3.50)	Age Squared	-0.000*** (-3.53)
Employment Status: Unemployed	-0.006 (-0.80)	Employment Status: Unemployed	-0.006 (-0.78)	Employment Status: Unemployed	-0.006 (-0.79)
Employment Status: Employed	-0.024*** (-3.25)	Employment Status: Employed	-0.024*** (-3.24)	Employment Status: Employed	-0.024*** (-3.25)
Highest Education: Primary	0.015 (0.55)	Highest Education: Primary	0.015 (0.55)	Highest Education: Primary	0.015 (0.55)
Highest Education: Grades 8-9	0.011 (0.33)	Highest Education: Grades 8-9	0.011 (0.33)	Highest Education: Grades 8-9	0.011 (0.32)
Highest Education: NQF 2-4	0.016 (0.46)	Highest Education: NQF 2-4	0.016 (0.47)	Highest Education: NQF 2-4	0.016 (0.46)
Highest Education: Tertiary Education	0.008 (0.22)	Highest Education: Tertiary Education	0.008 (0.22)	Highest Education: Tertiary Education	0.007 (0.21)
Married/Partner Living Together	-0.017** (-2.07)	Married/Partner Living Together	-0.017** (-2.07)	Married/Partner Living Together	-0.018** (-2.06)
Log of Real Household	-0.016*** (-4.41)	Log of Real Household	-0.016*** (-4.42)	Log of Real Household	-0.017*** (-4.43)

Income Per Capita		Income Per Capita		Income Per Capita	
Receipt of Government Grant	-0.013 (-2.08)	Receipt of Government Grant	-0.013** (-2.09)	Receipt of Government Grant	-0.013** (-2.07)
Geo Type: Urban	0.032** (2.54)	Geo Type: Urban	0.032** (-2.52)	Geo Type: Urban	0.032*** (2.57)
Geo Type: Farm	0.037* (1.95)	Geo Type: Farm	0.037* (1.95)	Geo Type: Farm	0.037** (1.98)
Household Size	-0.003** (-2.54)	Household Size	-0.003** (-2.52)	Household Size	-0.003*** (-2.53)
Entropy Balanced	Yes	Entropy Balanced	Yes	Entropy Balanced	Yes
N	85,958	N	85,958	N	85,958

Notes: All figures correct to 3 decimal places. Statistical significance is indicated by * at the 10%, ** at the 5%, and *** at the 1% level. Models estimated using linear fixed effects regression. Cluster-robust standard errors are clustered at the individual level. Individual, gender, race, month, wave, and provincial fixed effects absorbed through *reghdfe* command in Stata 17.

Table F2. Robustness Check 2: Poisson Regression for Count Data

Panel A: Hypothesis 1		Panel B: Hypothesis 2		Panel C: Hypothesis 3	
Variable	**(1) FDF IRR (z-statistic)**	**Variable**	**(2) FDF IRR (z-statistic)**	**Variable**	**(3) FDF IRR (z-statistic)**
Smoker	1.115*** (4.71)	Smoker	1.115*** (4.72)	Smoker	1.133*** (4.70)
Ban	1.037 (0.18)	Ban	1.037 (0.18)	Ban	1.045 (0.21)
Smoker x Ban	1.097 (1.11)	Smoker x Ban	0.800 (-1.03)	Smoker x Ban	0.956 (-0.42)
		Smoker x Ban x Continuer	1.434* (1.65)	Smoker x Female	0.919* (-1.77)
				Ban x Female	0.932 (-0.86)
				Smoker x Ban x Female	1.685*** (3.42)
Age	1.021 (1.21)	Age	1.021 (1.21)	Age	1.023 (1.30)
Age Squared	0.999*** (-5.62)	Age Squared	0.999*** (-5.61)	Age Squared	0.999*** (-5.70)
Employment Status: Unemployed	0.976 (-1.12)	Employment Status: Unemployed	0.976 (-1.10)	Employment Status: Unemployed	0.976 (-1.12)
Employment Status: Employed	0.897*** (-5.03)	Employment Status: Employed	0.898*** (-5.00)	Employment Status: Employed	0.897*** (-5.03)
Highest Education: Primary	0.994 (-0.09)	Highest Education: Primary	0.994 (-0.09)	Highest Education: Primary	0.991 (-0.13)
Highest Education: Grades 8-9	1.057 (0.51)	Highest Education: Grades 8-9	1.047 (0.51)	Highest Education: Grades 8-9	1.044 (0.48)
Highest Education: NQF 2-4	1.107 (1.10)	Highest Education: NQF 2-4	1.108 (1.11)	Highest Education: NQF 2-4	1.103 (1.05)
Highest Education: Tertiary Education	1.075 (0.76)	Highest Education: Tertiary Education	1.075 (0.77)	Highest Education: Tertiary Education	1.068 (0.70)
Married/Partner Living Together	0.931*** (-2.61)	Married/Partner Living Together	0.931*** (-2.62)	Married/Partner Living Together	0.932** (-2.55)
Log of Real Household Income Per Capita	0.935*** (-5.90)	Log of Real Household Income Per Capita	0.935*** (-5.89)	Log of Real Household Income Per Capita	0.934*** (-5.93)
Receipt of Government Grant	0.956** (-2.22)	Receipt of Government Grant	0.956** (-2.21)	Receipt of Government Grant	0.955** (-2.23)

Geo Type: Urban	1.056 (1.40)	Geo Type: Urban	1.057 (1.42)	Geo Type: Urban	1.057 (1.42)
Geo Type: Farm	1.075 (1.19)	Geo Type: Farm	1.075 (1.19)	Geo Type: Farm	1.078 (1.24)
Household Size	0.987*** (-3.32)	Household Size	0.987*** (-3.48)	Household Size	0.987*** (-3.31)
Entropy Balanced	Yes	Entropy Balanced	Yes	Entropy Balanced	Yes
N	74,099	N	74,099	N	74,099

Notes: All figures correct to 3 decimal places. Statistical significance is indicated by * at the 10%, ** at the 5%, and *** at the 1% level. Models estimated using Poisson regression with fixed effects. Cluster-robust standard errors are clustered at the individual level. Individual, gender, race, month, wave, and provincial fixed effects absorbed through *ppmlhdfe* command in Stata 17. IRR is the incidence-rate ratio, equal to the exponent of the estimated coefficient.

Table F3. Linear Regression with the Poisson Sub-Sample

Panel A: Hypothesis 1		Panel B: Hypothesis 2		Panel C: Hypothesis 3	
Variable	**(1) FDF IRR (z-statistic)**	**Variable**	**(2) FDF IRR (z-statistic)**	**Variable**	**(3) FDF IRR (z-statistic)**
Smoker	0.076*** (3.84)	Smoker	0.077*** (3.86)	Smoker	0.087*** (3.85)
Ban	0.025 (0.15)	Ban	0.025 (0.15)	Ban	0.035 (0.21)
Smoker x Ban	0.064 (0.92)	Smoker x Ban	-0.178 (-1.12)	Smoker x Ban	-0.034 (-0.41)
		Smoker x Ban x Continuer	0.278* (1.69)	Smoker x Female	-0.056 (-1.30)
				Ban x Female	-0.051 (-0.85)
				Smoker x Ban x Female	0.436*** (2.92)
Entropy Balanced	Yes	Entropy Balanced	Yes	Entropy Balanced	Yes
Controls	Yes	Controls	Yes	Controls	Yes
N	74,099	N	74,099	N	74,099

Notes: All figures correct to 3 decimal places. Statistical significance is indicated by * at the 10%, ** at the 5%, and *** at the 1% level. Models estimated using linear fixed effects regression. Individual, gender, race, month, wave, and provincial fixed effects absorbed through *reghdfe* command in Stata 17. All individual- and household-level controls included but not reported (available on request).

Table F3 presents the results of re-estimating our baseline linear fixed effects models with the sub-sample utilised for Poisson regression. As Poisson regression drops separated observations, this means the sample excludes individuals in the sample who never report depressive feelings therefore our sample composition changes. The sub-sample of individuals could therefore be considered as both the least sensitive to changes in their circumstances affecting their mental health, and individuals who at some point have experienced some depressive feelings. As such, we may expect the smokers in this sub-sample to be more sensitive to the changes in their mental health as a result of the ban.

We therefore re-ran our baseline linear models on this sub-sample of non-separated individuals to see if this significantly effects our baseline results. Unsurprisingly, we find the point DD estimates from each model to increased somewhat with this sub-sample. For model 1, the coefficient on the

interaction between smoking and the ban increased from 0.058 to 0.064 (remaining statistically insignificant). For model 2, the coefficient on our triple interaction between smoking, the ban, and continuing smoking increased from 0.243 to 0.279. For model 3, the coefficient on our triple interaction between smoking, the ban, and female increased from 0.395 to 0.436. This suggests that our treated individuals who have previously exhibited either fluctuations in their depressive feelings, or consistently reported at least mild levels of depressive feelings, may be more somewhat slightly more sensitive to the effects of the ban. Equally, this confirms that the results from the Poisson model were not simply due to our change in sample composition, and do in-fact reflect robustness in our baseline results between treating frequency of depressive feelings as continuous and as count data.

Table F4. Robustness Check 3: Linear Regression Excluding History of Depression

Panel A: Hypothesis 1			Panel B: Hypothesis 2			Panel C: Hypothesis 3		
Variable	**(1) FDF Exc. Strong History**	**(2) FDF Exc. Recent History**	**Variable**	**(3) FDF Exc. Strong History**	**(4) FDF Exc. Recent History**	**Variable**	**(5) FDF Exc. Strong History**	**(6) FDF Exc. Recent Hisotry**
	Coefficient (z-statistic)	**Coefficient (z-statistic)**		**Coefficient (z-statistic)**	**Coefficient (z-statistic)**		**Coefficient (z-statistic)**	**Coefficient (z-statistic)**
Smoker	0.060*** (3.42)	0.056*** (3.25)	Smoker	0.059*** (3.39)	0.057*** (3.27)	Smoker	0.059*** (3.01)	0.057*** (2.88)
Smoke Ban	-0.099 (-0.68)	-0.080 (-0.55)	Ban	-0.100 (-0.68)	-0.080 (-0.55)	Ban	-0.099 (-0.67)	-0.080 (-0.54)
Smoker x Smoke Ban	0.066 (1.12)	0.067 (1.14)	Smoker x Ban	-0.125 (-0.93)	-0.121 (-0.90)	Smoker x Ban	-0.007 (-0.11)	-0.005 (-0.07)
			Smoker x Ban x Continuer	0.220 (1.57)	0.216 (1.54)	Smoker x Female	0.002 (0.06)	0.004 (0.11)
						Ban x Female	-0.015 (-0.28)	-0.013 (-0.25)
						Smoker x Ban x Female	0.363*** (2.67)	0.358*** (2.63)
Age	0.022* (1.72)	0.020 (1.62)	Age	0.021* (1.71)	0.020 (1.62)	Age	0.022* (1.77)	0.021* (1.68)
Age Squared	-0.000*** (-4.77)	-0.000*** (-4.92)	Age Squared	-0.000*** (-4.76)	-0.000*** (-4.91)	Age Squared	-0.000*** (-4.85)	-0.000*** (-5.00)
Employment Status: Unemployed	-0.017 (-0.97)	-0.013 (-0.78)	Employment Status: Unemployed	-0.016 (-0.93)	-0.013 (-0.77)	Employment Status: Unemployed	-0.016 (-0.94)	-0.013 (-0.78)

Employment Status: Employed	-0.063*** (-3.65)	-0.062*** (-3.61)	Employment Status: Employed	-0.062*** (-3.60)	-0.062*** (-3.60)	Employment Status: Employed	-0.062*** (-3.61)	-0.062*** (-3.61)
Highest Education: Primary	-0.026 (-0.42)	-0.015 (-0.26)	Highest Education: Primary	-0.028 (-0.46)	-0.016 (-0.26)	Highest Education: Primary	-0.028 (-0.46)	-0.016 (-0.26)
Highest Education: Grades 8-9	0.009 (0.11)	0.008 (0.10)	Highest Education: Grades 8-9	0.007 (0.09)	0.008 (0.10)	Highest Education: Grades 8-9	0.007 (0.08)	0.007 (0.10)
Highest Education: NQF 2-4	0.054 (0.67)	0.053 (0.68)	Highest Education: NQF 2-4	0.052 (0.65)	0.053 (0.68)	Highest Education: NQF 2-4	0.051 (0.64)	0.052 (0.66)
Highest Education: Tertiary Education	0.051 (0.63)	0.049 (0.61)	Highest Education: Tertiary Education	0.049 (0.61)	0.048 (0.61)	Highest Education: Tertiary Education	0.047 (0.59)	0.047 (0.59)
Married/Partner Living Together	-0.034 (-1.63)	-0.033 (-1.62)	Married/Partner Living Together	-0.034 (-1.63)	-0.033 (-1.62)	Married/Partner Living Together	-0.033 (-1.60)	-0.033 (-1.59)
Log of Real Household Income Per Capita	-0.042*** (-4.69)	-0.042*** (-4.72)	Log of Real Household Income Per Capita	-0.042*** (-4.66)	-0.042*** (-4.73)	Log of Real Household Income Per Capita	-0.042*** (-4.68)	-0.042*** (-4.74)
Receipt of Government Grant	-0.024 (-1.52)	-0.022 (-1.44)	Receipt of Government Grant	-0.025 (-1.59)	-0.022 (-1.44)	Receipt of Government Grant	-0.024 (-1.57)	-0.022 (-1.43)
Geo Type: Urban	0.011 (0.36)	0.014 (0.47)	Geo Type: Urban	0.028 (1.05)	0.014 (0.48)	Geo Type: Urban	0.028 (1.07)	0.015 (0.51)
Geo Type: Farm	0.021 (0.48)	0.022 (0.49)	Geo Type: Farm	0.037 (0.88)	0.021 (0.48)	Geo Type: Farm	0.039 (0.92)	0.023 (0.53)
Household Size	-0.008*** (-2.74)	-0.008*** (2-.82)	Household Size	-0.008*** (-2.65)	-0.008*** (-2.79)	Household Size	-0.007*** (-2.66)	-0.009*** (-2.79)
Entropy Balanced	Yes	Yes	Entropy Balanced	Yes	Yes	Entropy Balanced	No	Yes

Controls	Yes	Yes	Controls	Yes	Yes	Controls	Yes	Yes
N	80,139	80,139	N	80,139	80,139	N	80,139	80,139

Notes: All figures correct to 3 decimal places. Statistical significance is indicated by * at the 10%, ** at the 5%, and *** at the 1% level. Models estimated using linear fixed effects regression. New entropy balanced sample weights were obtained for the new estimation sub-samples. Models estimated using linear fixed effects regression. Cluster-robust standard errors are clustered at the individual level. Individual, gender, race, month, wave, and provincial fixed effects absorbed through *ppmlhdfe* command in Stata 17.

Appendix 2G: Derivation of the Analytical Sample and Comparison with Missing Observations

Figure G1. Derivation of the Analytical Sample from the NIDS and NIDS-CRAM

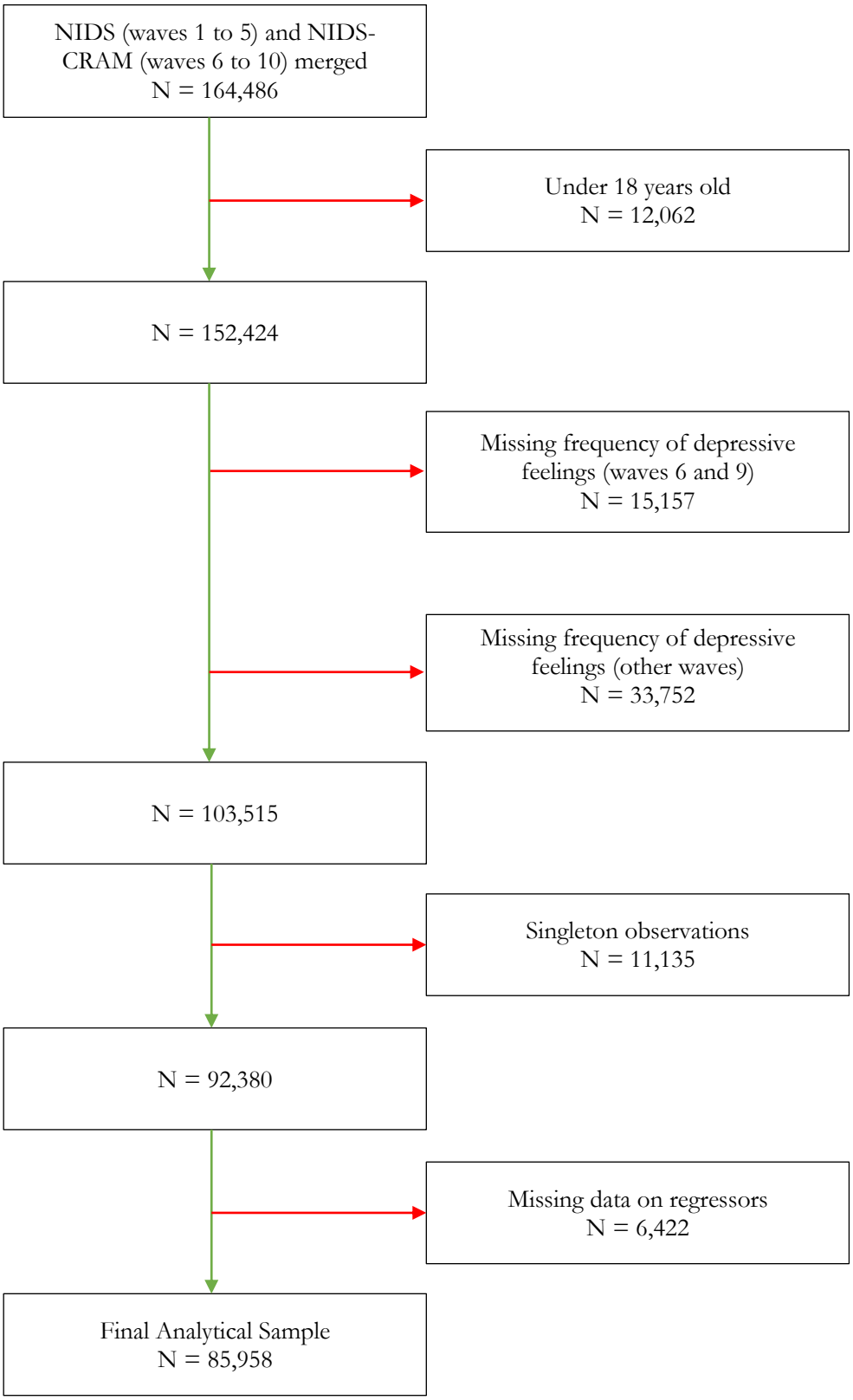


Table G1. Descriptive Statistics for Analytical Sample and Missing Observations

Variable	Analytical Sample		Missing Sample		Difference in Mean
	N	Mean	N	Mean	
Frequency of Depressive Feelings	85,958	0.627	17,557	0.594	0.034***
Frequency of Depressive Feelings = 0	85,958	0.562	17,557	0.596	-0.033***
Frequency of Depressive Feelings = 1	85,958	0.289	17,557	0.262	0.027***
Frequency of Depressive Feelings = 2	85,958	0.109	17,557	0.096	0.013***
Frequency of Depressive Feelings = 3	85,958	0.041	17,557	0.047	-0.006****
Smoker	85,958	0.184	17,653	0.187	-0.004
Continuer	85,958	0.005	17,653	0.007	-0.002***
Tobacco Sales Ban	85,958	0.045	51,309	0.058	-0.013***
Female	85,958	0.612	45,567	0.497	0.115***
Race: Black African	85,958	0.828	45,580	0.702	0.126***
Race: Coloured	85,958	0.132	45,580	0.150	-0.018***
Race: Asian/Indian	85,958	0.010	45,580	0.029	-0.018***
Race: White	85,958	0.030	45,580	0.120	-0.090
Age	85,958	40.430	45,589	38.425	2.006***
Employment Status: Not Economically Active	85,958	0.409	24,031	0.402	0.007**
Employment Status: Unemployed	85,958	0.187	24,031	0.214	-0.028***
Employment Status: Employed	85,958	0.405	24,031	0.384	0.020***
Highest Education: No Schooling	85,958	0.102	33,910	0.091	0.011***
Highest Education: Primary	85,958	0.200	33,910	0.170	0.030***
Highest Education: Grades 8-9	85,958	0.141	33,910	0.144	-0.003
Highest Education: NQF 2-4	85,958	0.386	33,910	0.456	-0.070***
Highest Education: Tertiary	85,958	0.171	33,910	0.140	0.031***
Marital Status: Married or Living with Partner	85,958	0.357	28,872	0.327	0.030***
Real Total Monthly Household Income Per Capita	85,958	1268R	38,783	2247R	-979R***
Log of Real Total Monthly Household Income Per Capita	85,958	6.473R	38,783	6.640R	-0.167R***
Household Receipt of Government Grant	85,958	0.681	30,680	0.631	0.050***
Geo-type: Traditional	85,958	0.404	40,001	0.302	0.102***
Geo-type: Urban	85,958	0.533	40,001	0.629	-0.097***
Geo-type: Farm	85,958	0.064	40,001	0.069	-0.005***
Household Size	85,958	5.266	30,989	5.549	-0.283***

Notes: All figures correct to three decimal places. Statistical significance in difference in means *t*-test is indicated by * at the 10%, ** at the 5%, and *** at the 1% level.

Appendix 3: Chapter Four

Appendix 3A: Description of Variables

Table A1. Description of Variables

Variable	Description	Notes	Type	Waves	Expected Association with MHI-5
Dependent Variable					
MHI-5	Continuous variable on a scale of 0 to 100 with higher scores indicative of better mental health.	The five-item Mental Health Inventory (MHI-5) is constructed as a sub-scale from the 36-item Short Form Survey (SF-36). The five items are: "Have you been a nervous person?", "Have you felt so down in the dumps that nothing could cheer you up?", "Have you felt calm and peaceful?", "Have you felt downhearted and blue?", and "Have you been a happy person?". Responses are on a 6-point Likert scale from "All of the time" (=1) to "None of the time" (=6). Responses are then summed, with items 2 and 5 reverse coded, producing a total score of from 5 to 30 with higher scored reflecting better mental health. This is then transformed into a variable from 0 to 100 through standard linear transformation. Used as the primary outcome variable in the analysis.	Continuous	1-21	N/A
Personality					
Extroversion (Normalised)	Continuous variable reflecting the level of extroversion of an individual on a scale of 0 (least) to 1 (most).	Individuals are asked 36 questions pertaining to their personality, with each question rated on a 7-point scale from = 1 'Does not describe me at all' to = 7 'Described me very well'. The downloaded data has already utilised these to derive an index for each of the 'Big 5' personality traits, with each index on a continuous scale from 1 to 7 representing the average score across the items pertaining to that personality trait. Higher scores are indicative of the better that personality trait describes the respondent. For extroversion, the items are: Talkative, Bashful (reversed), Quiet (reversed), Shy (reversed), Lively, and Extroverted. First observed in wave 5 and then subsequently every four waves. For the analysis, we impute forward the last observed response for the three waves between subsequent observations. We also rescale the variable to 0 to 1.		5, 9, 13, 17, 21	Positive

Variable	Description	Notes	Type	Waves	Expected Association with MHI-5
		Personality variables are demeaned by lockdown cohort-time mean values when interacted with the time-varying treatment indicator in the ETWFE model.			
Emotional Stability (Normalised)	Continuous variable reflecting the level of emotional stability of an individual on a scale of 0 (least) to 1 (most).	Individuals are asked 36 questions pertaining to their personality, with each question rated on a 7-point scale from = 1 'Does not describe me at all' to = 7 'Described me very well'. The downloaded data has already utilised these to derive an index for each of the 'Big 5' personality traits, with each index on a continuous scale from 1 to 7 representing the average score across the items pertaining to that personality trait. Higher scores are indicative of the better that personality trait describes the respondent. For emotional stability, the items are: Envious (reversed), Moody (reversed), Touchy (reversed), Jealous (reversed), Temperamental (reversed) and Fretful (reversed). First observed in wave 5 and then subsequently every four waves. For the analysis, we impute forward the last observed response for the three waves between subsequent observations. We also rescale the variable to 0 to 1. Personality variables are demeaned by lockdown cohort-time mean values when interacted with the time-varying treatment indicator in the ETWFE model.		5, 9, 13, 17, 21	Positive
Agreeableness (Normalised)	Continuous variable reflecting the level of agreeableness of an individual on a scale of 0 (least) to 1 (most).	Individuals are asked 36 questions pertaining to their personality, with each question rated on a 7-point scale from = 1 'Does not describe me at all' to = 7 'Described me very well'. The downloaded data has already utilised these to derive an index for each of the 'Big 5' personality traits, with each index on a continuous scale from 1 to 7 representing the average score across the items pertaining to that personality trait. Higher scores are indicative of the better that personality trait describes the respondent. For agreeableness, the items are: Sympathetic, Kind, Cooperative, and Warm. First observed in wave 5 and then subsequently every four waves. For the analysis, we impute forward the last observed response for the three waves between subsequent observations. We also rescale the variable to 0 to 1.		5, 9, 13, 17, 21	Positive

Variable	Description	Notes	Type	Waves	Expected Association with MHI-5
		Personality variables are demeaned by lockdown cohort-time mean values when interacted with the time-varying treatment indicator in the ETWFE model.			
Conscientiousness (Normalised)	Continuous variable reflecting the level of conscientiousness of an individual on a scale of 0 (least) to 1 (most).	Individuals are asked 36 questions pertaining to their personality, with each question rated on a 7-point scale from = 1 'Does not describe me at all' to = 7 'Described me very well'. The downloaded data has already utilised these to derive an index for each of the 'Big 5' personality traits, with each index on a continuous scale from 1 to 7 representing the average score across the items pertaining to that personality trait. Higher scores are indicative of the better that personality trait describes the respondent. For conscientiousness, the items are: Orderly, Systematic, Inefficient (reversed), Sloppy (reversed), Disorganised (reversed), and Efficient. First observed in wave 5 and then subsequently every four waves. For the analysis, we impute forward the last observed response for the three waves between subsequent observations. We also rescale the variable to 0 to 1. Personality variables are demeaned by lockdown cohort-time mean values when interacted with the time-varying treatment indicator in the ETWFE model.		5, 9, 13, 17, 21	Positive
Openness (Normalised)	Continuous variable reflecting the level of openness of an individual on a scale of 0 (least) to 1 (most).	Individuals are asked 36 questions pertaining to their personality, with each question rated on a 7-point scale from = 1 'Does not describe me at all' to = 7 'Described me very well'. The downloaded data has already utilised these to derive an index for each of the 'Big 5' personality traits, with each index on a continuous scale from 1 to 7 representing the average score across the items pertaining to that personality trait. Higher scores are indicative of the better that personality trait describes the respondent. For openness, the items are: Deep, Philosophical, Creative, Intellectual, Complex, and Imaginative. First observed in wave 5 and then subsequently every four waves. For the analysis, we impute forward the last observed response for the three waves between subsequent observations. We also rescale the variable to 0 to 1.		5, 9, 13, 17, 21	Positive

Variable	Description	Notes	Type	Waves	Expected Association with MHI-5
		Personality variables are demeaned by lockdown cohort-time mean values when interacted with the time-varying treatment indicator in the ETWFE model.			
Lockdown Indicators					
Extended Lockdown Cohort 2020	Binary variable = 1 if individual first under an extended lockdown in 2020, = 0 otherwise.	Applies to individuals residing Victoria in wave 20, and takes the value of 1 for all waves. In the ETWFE model, this is denoted by: d_{2020} As we use fixed effects estimation, the variable is omitted from the model.	Binary	1-21	Omitted
Extended Lockdown Cohort 2021	Binary variable = 1 if individual was first under an extended lockdown in 2021, = 0 otherwise.	Applies to individuals residing in NSW, and ACT, and takes the value of 1 for all waves. In the ETWFE model, this is denoted by d_{2021}. As we use fixed effects estimation, the variable is omitted from the model.	Binary	1-21	Omitted
Extended Lockdown	Binary variable = 1 if individual was under extended lockdown, = 0 otherwise.	Time-varying treatment indicator = 1 for residents of Victoria in wave 20 and 21, and for residents of NSW and ACT in wave 21. In the ETWFE model, this is denoted by: W_{it} This is only directly used to test the no anticipation assumption.	Binary	1-21	Not Used
Cohort 2020: Extended Lockdown 2020	Binary variable = 1 if individual was in the 2020 extended lockdown cohort and was under extended lockdown in wave 20, = 0 otherwise	Applies to individuals residing in Victoria and is time-varying such that it only equals 1 in wave 20, and 0 in all other waves. In the ETWFE model, this is denoted by $w2020_{20}$, and is the product of d_{2020} x W_{it} x fs_{20}, where fs_{20} is an indicator for wave 20. This is the variable giving the ATT for residents of Victoria under the 2020 extended lockdown.	Binary	1-21	Negative
Cohort 2020: Extended Lockdown 2021	Binary variable = 1 if individual was in the 2020 extended lockdown cohort and was under extended lockdown in wave 21, = 0 otherwise	Applies to individuals residing in Victoria and is time-varying such that it only equals 1 in wave 21, and 0 in all other waves. In the ETWFE model, this is denoted by $w2020_{21}$, and is the product of d_{2020} x W_{it} x fs_{21}, where fs_{21} is an indicator for wave 21. This is the variable giving the ATT for residents of Victoria under the 2021 extended lockdown.	Binary	1-21	Negative
Cohort 2021: Extended Lockdown 2021	Binary variable = 1 if individual was in the 2021 extended	Applies to individuals residing in NSW and ACT and is time-varying such that it only equals 1 in wave 21, and 0 in all other waves.	Binary	1-21	Negative

Variable	Description	Notes	Type	Waves	Expected Association with MHI-5
	lockdown cohort and was under extended lockdown in wave 21, = 0 otherwise	In the ETWFE model, this is denoted by $w2021_{21}$, and is the product of d_{2021} x W_{it} x fs_{21}, where fs_{21} is an indicator for wave 21. This is the variable giving the ATT for residents of NSW and ACT under the 2021 extended lockdown.			
OxCGRT Variables					
OxCGRT Stringency Index	Continuous variable for the OxCGRT Stringency Index value on date of interview.	The OxCGRT Stringency Index is available from 1 January to 31 December 2022, and is constructed from the 8 'Closure and containment indicators' plus 1 'Health indicator'. Specifically, the 'Closure and containment indicators' are: 'School closing', 'Workplace closing', 'Cancellation of public events', 'Limits on gatherings', 'Closing of public transport', 'Stay at home requirements', Restrictions on internal movement', and 'Restrictions on international travel'. The one 'Health indicator' is 'Presence of public information campaigns'. Each item is scored on an ordinal scale with a minimum score of 0 indicating absence of policy, and varying maximum scores of 3, 4, or 5 indicating strongest level of policy. This information is aggregated to construct an index, which is then normalised on a scale of 0 to 100. Full details of the construction of the index are available from Hale *et al.* (2023). We assign the stringency index by date of SCQ completion to individuals at the GCCSA level. Where GCCSA is available at the State Capital and Rest of State level, the 'City Total' index is assigned (applies to Victoria, NSW, Queensland, SA, and WA). Where GCCSA is only available at the whole state/territory level, the 'State Total' index is assigned (applies to NT, Tasmania, and ACT). Pre-covid waves (waves 1-19) are assigned a score of 0. The OxCGRT data for Australia was obtained from: https://github.com/OxCGRT/Australia-covid-policy	Continuous	1-21	Negative
State COVID-19 Deaths	Continuous variable for the cumulative recorded State-level COVID-19 deaths.	The OxCGRT dataset also provides daily information on the cumulative recorded COVID-19 deaths and cases at the state-level. These were assigned to individuals by date of completion of the SCQ at the household state level. The data were obtained from https://github.com/OxCGRT/Australia-covid-policy. Pre-covid waves (waves 1-19) are assigned a count of 0.	Continuous	1-21	Negative
State COVID-19 Cases	Continuous variable for the cumulative	The OxCGRT dataset also provides daily information on the cumulative recorded COVID-19 deaths and cases at the state-level. These were assigned to individuals by date of completion of the SCQ at the	Continuous	1-21	Negative

Variable	Description	Notes	Type	Waves	Expected Association with MHI-5
	recorded State-level COVID-19 cases.	household state level. The data were obtained from https://github.com/OxCGRT/Australia-covid-policy. Pre-covid waves (waves 1-19) are assigned a count of 0.			
Individual- and Household-Level Control Variables					
Male	Binary variable = 1 if individual is male, = 0 otherwise	Individual's gender. Time-invariant therefore excluded from fixed effects models unless interacted with other variables.	Binary	1-21	Positive
Age Group	Ordinal variable for age group.	We use age groups based on Li *et al.* (2023) to avoid collinearity issues with wave and time indicators used in the analysis. The age groups defined are: =1 if 15 to 24 years old, = 2 if 25 to 34 years old, = 3 if 35 to 44 years old, = 4 if 45 to 54 years old, = 5 if 55 to 64 years old, = 6 if 65 years old or over. Binary indicators for each age category are utilised in the analysis, with 15-24 year olds omitted as the reference category variable.	Ordinal	1-21	Negative
Education Level: Year 12 or Above	Binary variable = 1 if individual has attained Year 12 education or above, = 0 otherwise	Year 12 education is the final year of school education in Australia (usually ages 17-18). Education becomes non-compulsory after Year 10 (usually ages 15-16).	Binary	1-21	Positive
Marital Status: Married	Binary variable = 1 if individual is legally married, = 0 otherwise.	Marital status is measured by the following categories: = 1 if "Legally Married", = 2 if "In a De Facto Relationship", = 3 if "Seperated", = 4 if "Divorced", = 5 if "Widowed", = 6 if "Never Married". Married is omitted as the reference category in models.	Binary	1-21	Omitted
Marital Status: De Facto Relationship	Binary variable = 1 if individual is in a de facto relationship, = 0 otherwise.	A "De Facto Relationship" captures individuals who live with their partner but are not legally married. None.	Binary	1-21	Not Significant
Marital Status: Separated	Binary variable = 1 if individual is separated from a partner, = 0 otherwise.	None.	Binary	1-21	Negative
Marital Status: Divorced	Binary variable = 1 if individual is divorced, = 0 otherwise.	None.	Binary	1-21	Negative

Variable	Description	Notes	Type	Waves	Expected Association with MHI-5
Marital Status: Widowed	Binary variable = 1 if individual is widowed, = 0 otherwise.	None.	Binary	1-21	Negative
Marital Status: Never Married	Binary variable = 1 if individual is single (and has never been married), = 0 otherwise.	None.	Binary	1-21	Negative
Labour Force Status: Employed	Binary variable = 1 if individual is employed, = 0 otherwise	Based on the broad labour force status definitions of employed, unemployed, or not economically active. Employed is omitted as the reference category in the models.	Binary	1-21	Omitted
Labour Force Status: Unemployed	Binary variable = 1 if individual is unemployed, = 0 otherwise	None.	Binary	1-21	Negative
Labour Force Status: Not Economically Active	Binary variable = 1 if individual is not economically active, = 0 otherwise	None.	Binary	1-21	Negative
Real Household Income Per Capita	Continuous variable for real household monthly disposable income per household member.	Household disposable income is provided in the HILDA and the summation of individual monthly disposable income. Disposable income is calculated as total income after receipt of government benefits and deduction of income tax (Summerfield *et al.*, 2021). It is possible for disposable income to be negative in the data, which tends to occur if income is derived from businesses reporting losses (La Cava and Simon, 2003). We remove households with negative disposable income from the data, and also winsorised the 1% tails of the income distribution to remove outliers. The income variable was then adjusted to April 2022 prices using quarterly CPI figures available from https://fred.stlouisfed.org/tags/series?t=australia%3Bcpi. Finally, the total household disposable income figure was divided by the number of household members to produce a 'per capita' figure.	Continuous	1-21	Not Used
Log of Real Household Income Per Capita	Natural logarithm of real household income per capita.	For the analysis we use the natural logarithm for real household disposable income per capita to account for skewness.	Continuous	1-21	Positive

Variable	Description	Notes	Type	Waves	Expected Association with MHI-5
Smoker	Binary variable = 1 if individual is a weekly smoker, = 0 otherwise	The HILDA categorises smokers as: 'never smokers' = 1, 'ex-smokers' = 2, 'less than weekly smokers' = 3, 'weekly smokers' = 4, and 'daily smokers' = 5. We define a binary variable equal to 1 if the individual smokes cigarettes weekly or more, and 0 otherwise.	Binary	1-21	Negative
Drinker	Binary variable = 1 if individual is a weekly drinker, = 0 otherwise	The HILDA categorises alcohol consumption as: 'never drunk alcohol' = 1, 'no longer drinks alcohol' = 2, 'rarely drinks alcohol' = 3, 'drinks 2 to 3 days per month' = 4, 'drinks 1 to 2 days per week' = 5, 'drinks 3 to 4 days per week' = 6, 'drinks 5 to 6 days per week' = 7, and 'drinks every day' = 8. We define a binary variable equal to 1 if the individual drinks weekly or more, and 0 otherwise.	Binary	1-21	Negative
Self-Rated Health	Ordinal variable for individuals' self-rated health on a scale of 1 to 5.	Self-rated Health is measured on a five-point scale: = 1 if "Poor", = 2 if "Fair", = 3 if "Good", = 4 if "Very Good", = 5 if "Excellent" Binary indicators for each response level are utilised in the analysis, with "Poor" omitted as the reference category variable.	Ordinal	1-21	Positive
Long-Term Health Condition	Binary variable = 1 if individual has a long-term health condition which restricts their everyday activities, = 0 otherwise	The condition must have lasted or be expected to last at least 6 months or more. Respondents are shown a showcard with multiple conditions and asked if they have any of them.	Binary	3-21	Negative
Social Support Index	Continuous variable for the level of social support reported by the individual.	Social support is measured through 10 items, the first 7 of which are from Henderson *et al.* (1978) and the last three from Marshall & Barnett (1993). There are five negatively framed and five positively framed statements. Each item is rated on a 7-point scale indicating strength of agreement. The negatively framed questions have been coded so 1 is 'Strongly Agree' and 7 is 'Strongly Disagree', and vice versa for the positively framed questions. The index has then been generated as the sum of scores across the 10 items, producing a scale from 10 (lowest social support) to 70 (highest social support).	Continuous	1-21	Positive
Frequency of Social Interaction	Ordinal variable for frequency of social interaction.	Social frequency reflects the individual's answer to how often they get together with friends or relative (not living with them), with 7 possible answers: = 1 if "Less often than once every 3 months", = 2 if "Once or twice every 3 months", = 3 if "About once a month", = 4 if "2 or 3 times a month", = 5 if "About once a week", = 6 if "Several times a week", = 7 if "Every day".	Ordinal	1-21	Positive

Variable	Description	Notes	Type	Waves	Expected Association with MHI-5
		Binary indicators for each response level are utilised in the analysis, with "Less often than once evert 3 months" omitted as the reference category variable.			
Self-Rated Financial Status	Ordinal variable for individual's self-rated family finanical circumstances.	Individuals are asked to indicate their family's financial situation given their current needs and financial responsibilities with 6 possible answers: = 1 if "Very Poor", = 2 if "Poor", = 3 if "Just Getting Along", = 4 if "Reasonably Comfortable", = 5 if "Very Comfortable", = 6 if "Prosperous". Binary indicators for each response level are utilised in the analysis, with "Very Poor" omitted as the reference category variable.	Ordinal	1-21	Positive
Any Negative Event	Binary variable = 1 if individual has experienced any negative life event in the past 12 months, = 0 otherwise	Individuals are asked to report if they have experienced any of the following negative life events in the past 12 months: 'Serious personal injury or illness', 'Serious injury or illness to family member', 'Death of a spouse or child', 'Death of a close relative or family member (non-spouse or child)', 'Death of a close friend', Victim of violence', 'Victim of property crime', 'Detained in jail', 'Family member detained in jail', 'Fired or made redundant from job', or 'Major worsening of finances'.	Binary	1-21	Negative
Family Relationship	Categorical (Nominal)	Family relationship captures the individual's status within a household in the following manner: = 1 if 'Couple with child <15', = 2 if 'Couple with dependent student', = 3 if 'Couple with non-dependent child', = 4 if 'Couple without child < 15', = 5 if 'Lone parent with child <15', = 6 if 'Lone parent with dependent student', = 7 if 'Lone parent with non-dependent child', = 8 if 'Child <15', = 9 if 'Dependent student', = 10 if 'Non-dependent child', = 11 if 'Other family member', = 12 if 'Lone person', = 13 if 'Unrelated to all household members'. A couple is a married couple or in a de facto relationship. Children are classified as individuals aged under 15. Dependent students are those aged 15-24 who are studying full-time, not working full-time, and live in a household with their parent/guardian. Non-dependent children are children aged over 15 who do not fall into the category of dependent students. Other related is another family member who is not part of a couple or parent-child relationship but is related to other members of the household. A lone person is a single-person household. Non-family member is a person who is not related to any other members of the household (*e.g.*, a house share). A couple relationship takes precedence over a parent-child relationship. The most recent generation has	Categorical (Nominal)	1-21	N/A

Variable	Description	Notes	Type	Waves	Expected Association with MHI-5
		precedence overran older generation, with the older generation then considered as an 'other relative'. The youngest child takes precedence over older children (Summerfield *et al.*, 2021) Not Used in the Analysis.			
Family Relationship: Couple (<65 Years Old) Without Children (<15 Years Old)	Binary variable = 1 if individual is aged under 65 and in a couple without children under 15 years old, = 0 otherwise	Binary variable defined to equal 1 if individual under 65 years old and either a 'Couple with dependent student', 'Couple with non-dependent child', or 'Couple without a child < 15, and 0 otherwise. Note a couple is a married couple or in a de facto relationship. Children are classified as individuals aged under 15. Omitted as the reference category.	Binary	1-21	Omitted
Family Relationship: Couple with Child(ren) (<15 Years Old)	Binary variable = 1 if individuals is in a couple with child(ren) under 15 years old, 0 otherwise	Binary variable defined to equal 1 if individual is a 'Couple with child under 15', 0 otherwise. Note a couple is a married couple or in a de facto relationship. Children are classified as individuals aged under 15.	Binary	1-21	Negative
Family Relationship: Single Parent with Child(ren) (<15 Years Old)	Binary variable =1 if individual is a single parent with child(ren) under 15 years old, 0 otherwise	Binary variable defined to equal 1 if individual is a 'Lone parent with child < 15', 0 otherwise.	Binary	1-21	Negative
Family Relationship: Single Parent without Child(ren) (<15 Years Old)	Binary variable = 1 if individual is a single parents without child(ren) under 15 years old, = 0 otherwise	Binary variable defined to equal 1 if individual is a 'Lone parents with dependent student' or 'Lone parents with non-dependent child', = 0 otherwise.	Binary	1-21	Negative
Family Relationship: Single Person (< 65 Years Old)	Binary variable = 1 if individual is aged under 65 and is a single person, = 0 otherwise	Binary variable defined to equal 1 if individual is aged under 65 years old and a 'Lone person', = 0 otherwise. Note this reflects individuals without children of any age (including adult children and dependent students) residing in their household.	Binary	1-21	Negative
Family Relationship: Elderly Single Person	Binary variable = 1 if individual is aged 65	Binary variable defined to equal 1 if individual is aged over 65 years old and a 'Lone person', = 0 otherwise. Note this reflects individuals without	Binary	1-21	Negative

Variable	Description	Notes	Type	Waves	Expected Association with MHI-5
	or over and is a single person, = 0 otherwise	children of any age (including adult children and dependent students) residing in their household.			
Family Relationship: Elderly Couple	Binary variable = 1 if individuals is aged 65 or over and in a couple, = 0 otherwise	Binary variable defined to equal 1 if individual aged over 65 years old and either a 'Couple with dependent student', 'Couple with non-dependent child', or 'Couple without a child < 15, and 0 otherwise. Note a couple is a married couple or in a de facto relationship. Children are classified as individuals aged under 15.	Binary	1-21	Positive
Family Relationship: Dependent Student	Binary variable = 1 if individual is a dependent student, = 0 otherwise	Binary variable defined to equal 1 if individual is a 'Dependent student', 0 otherwise. Note a dependent student is an individual aged 15 to 24 years old in full-time education, not in full-time employment, and who does not have a partner or child of their own in the household.	Binary	1-21	Positive
Family Relationship: Non-Dependent Child (>15 Years Old)	Binary variable = 1 if individual is a non-dependent child, = 0 otherwise	Binary variable defined to equal 1 if individual is a 'Non-dependent child', and 0 otherwise. Note a non-dependent child is an individual aged 15 years old or above who lives in the household with their parents but is not categorised as a dependent student, and does not have a partner or child of their own in the household.	Binary	1-21	Positive
Family Relationship: Other Family Member	Binary variable = 1 if individual is an 'Other family member', = 0 otherwise.	Binary variable defined to equal 1 if individual is an 'Other family member', and 0 otherwise. Note an other family member is a person who is not part of a couple or parent-child relationship, but is related to other members of the household.	Binary	1-21	Negative
Family Relationship: Unrelated to Household Members	Binary variable = 1 if individual is 'Unrelated to all household members', = 0 otherwise	Binary variable defined to equal 1 if individual is 'Unrelated to all household members', and 0 otherwise.	Binary	1-21	Negative
Household Size: Children	Continuous variable for number of children (under 15 years old) residing in the household.	Children are defined as individuals aged under 15 years old.	Continuous	1-21	Positive
Household Size: Adults	Continuous variable for number of adults residing in the household.	None.	Continuous	1-21	Positive
Index of Relative Socioeconomic	Deciles for the Index of Relative	The Socioeconomic Indexes for Areas (SEIFA) Index of Relative Socioeconomic Advantage and Disadvantage (IRSAD) – 2021	Ordinal	1-21	Omitted

Variable	Description	Notes	Type	Waves	Expected Association with MHI-5
Advantage and Disadvantage (IRSAD)	Socioeconomic Advantage and Disadvantage (IRSAD)	definitions. A low score on the index indicates relatively greater disadvantage and a lack of advantage in general for the area (*e.g.*, many low-income households or many people in low skill occupations AND few households with high incomes or few people in skilled occupations). Individuals in the HILDA are group by their IRSAD decile. Thus, those in the lowest decile live in an area that is most disadvantaged and least advantaged and those in the highest decile live in an area that is least disadvantaged and most advantaged. Binary indicators for each decile used in the analysis, with decile 1 omitted as the reference category.			
Dwelling: Separate House	Binary variable = 1 if individual lives in a separate (detached) house, = 0 otherwise	This dwelling type includes 'Separate house' and 'Separate house with attached shop'. Omitted as reference category.	Binary	1-21	Omitted
Dwelling: Semi/Terrace/Townhouse	Binary variable = 1 if individual lives in a semi-detached, terrace, or townhouse, = 0 otherwise	This dwelling type includes 'Semi-detached house with one storey', 'Semi-detached house with two or more storeys', and 'Semi-detached house attached to a shop'	Binary	1-21	Negative
Dwelling: Flat	Binary variable = 1 if individual lives in a flat or apartment, = 0 otherwise	This dwelling type includes 'Flat/unit/apartment in one storey building', 'Flat/unit/apartment in two-storey building', 'Flat/unit/apartment in three storey building' 'Flat/unit/apartment in four to nine storey building', 'Flat/unit/apartment in ten or more storey building', 'Flat/unit/apartment attached to a house', 'Flat/unit/apartment attached to a shop, office etc.', and 'Flat (no further information)'.	Binary	1-21	Negative
Dwelling: Other	Binary variable = 1 if individual lives in another form of dwelling, = 0 otherwise	This dwelling type includes 'Non-private dwelling – nursing home', 'Non-private dwelling – other', 'Caravan/Tent/Cabin/Houseboat etc.'	Binary	1-21	Negative
Remoteness Area: Major City of Australia	Binary variable = 1 if household is located in a 'Major City of Australia', = 0 otherwise	The 'Remoteness Area' is defined by the Australian Statistical Geography Standard (ASGS) and is essentially a measure of proximity goods and services (see: https://meteor.aihw.gov.au/content/531713) Omitted as the reference category.	Binary	1-21	Omitted

Variable	Description	Notes	Type	Waves	Expected Association with MHI-5
Remoteness Area: Inner Regional Australia	Binary variable = 1 if household is located in 'Inner regional Australia', = 0 otherwise	The 'Remoteness Area' is defined by the Australian Statistical Geography Standard (ASGS) and is essentially a measure of proximity goods and services (see: https://meteor.aihw.gov.au/content/531713)	Binary	1-21	Negative
Remoteness Area: Outer Regional Australia	Binary variable = 1 if household is located in 'Outer regional Australia', = 0 otherwise	The 'Remoteness Area' is defined by the Australian Statistical Geography Standard (ASGS) and is essentially a measure of proximity goods and services (see: https://meteor.aihw.gov.au/content/531713)	Binary	1-21	Negative
Remoteness Area: Remote or Very Remote Australia	Binary variable = 1 if household is located in 'Remote or very remote Australia', = 0 otherwise	The 'Remoteness Area' is defined by the Australian Statistical Geography Standard (ASGS) and is essentially a measure of proximity goods and services (see: https://meteor.aihw.gov.au/content/531713)	Binary	1-21	Negative
Notes: Expected association of independent variables with frequency of depressive feelings are based on findings from the literature on socioeconomic determinants of depression (refs) and studies utilising NIDS and NIDS-CRAM data to conduct depression outcome regressions (refs). Expected association is based on point estimates from studies rather than statistical significance of estimate coefficients. Race and Gender indicators are omitted in linear fixed effects models but are still utilised in the analysis for entropy balancing and/or for interacting with smoking status and the tobacco ban indicator.					

Appendix 3B: Lockdown Dates

Table B1. Dates of Lockdowns in Victoria, New South Wales, and Australian Capital Territory

Lockdown Dates	HILDA Wave	First SCQ Return Date	Last SCQ Return Date	% SCQ Returned During Lockdown
Greater Melbourne				
9 July 2020 27 October 2020	20	10 April 2020	12 February 2021	96%
13 February 2021 17 February 2021	Between 20 and 21	N/A	N/A	N/A
28 May 2021 10 June 2021	21	5 April 2021	2 March 2022	0%
16 July 2021 27 July 2021	21	5 April 2021	2 March 2022	3%
5 August 2021 21 October 2021	21	5 April 2021	2 March 2022	80%
Rest of Victoria				
2 July 2020 17 October 2020	20	23 July 2020	12 February 2021	90%
13 February 2021 17 February 2021	Between 20 and 21	N/A	N/A	N/A
28 May 2021 10 June 2021	21	6 June 2021	2 March 2022	3%
16 July 2021 27 July 2021	21	6 June 2021	2 March 2022	1%
5 August 2021 10 September 2021	21	6 June 2021	2 March 2022	56%
Greater Sydney				
19 December 2020 9 January 2021	20	4 April 2020	26 February 2021	2%
26 June 2021 10 October 2021	21	14 June 2021	10 March 2022	91%
Rest of New South Wales				
14 August 2021 10 September 2021	21	27 July 2021	27 February 2022	56%
Australian Capital Territory				
12 August 2021 13 October 2021	21	13 July 2021	5 March 2022	68%

Notes: Extended lockdowns in bold. Dates are inclusive. December 2020 to January 2021 lockdown only applied to the Northern Beaches area of Greater Sydney. Some LGAs in Rest of NSW were placed under snap-lockdowns between 10 September and 8 October 2021.

Appendix 3C: Tests of Parallel Trends and No Anticipation Assumptions

Table C1. Test of Parallel Trends Assumption under ETWFE Framework

Variable	(1) Test of Parallel Trends (Unconditional on Covariates)	(2) Test of Parallel Trends (Conditional on Covariates)
	Coefficient (t-stat)	Coefficient (t-stat)
D2020 x T	0.048** (2.12)	-0.043 (-0.18)
D2021 x T	0.078*** (3.09)	-0.116 (-0.44)
F(2,12)	5.630***	0.110
Prob > F	0.018	0.900
Personality x D2020 x T	No	Yes
Covariates x D2020 x T	No	Yes
Time Fixed Effects	Yes	Yes
GCCSA Fixed Effects	Yes	Yes
Entropy Balanced	No	Yes
N	187,074	164,841

Notes: Coefficients correct to 3 decimal places, t-statistics to 2 decimal places. Statistical significance indicated by * at the 10%, ** at the 5%, and *** at the 1% level. Models estimated using fixed effects regression implemented with the *reghdfe* Stata command. Cluster-robust standard errors are clustered at the GCCSA level. Individual and GCCSA fixed effects are absorbed. Column 1 provides the test of the parallel trends assumption specified by *Equation (3)*. Column 2 provides the test of the parallel trends assumption allowing for heterogeneity in cohort-time trends conditional on covariates specified by *Equation (5)*.

Table C2. Test of No Anticipation Assumption under ETWFE Framework

Variable	(1) Test of No Anticipation
	Coefficient (t-stat)
Extended Lockdown *t+1*	-0.047 (-0.37)
Personality x T	Yes
Covariates x T	Yes
Time Fixed Effects	Yes
GCCSA Fixed Effects	Yes
Entropy Balanced	No
N	187,074

Notes: Coefficients correct to 3 decimal places, t-statistics to 2 decimal places. Statistical significance indicated by * at the 10%, ** at the 5%, and *** at the 1% level. Models estimated using fixed effects regression implemented with the *reghdfe* Stata command. Cluster-robust standard errors are clustered at the GCCSA level. Individual and GCCSA fixed effects are absorbed. Column 1 provides the results for the test of the no anticipation assumption specified by *Equation (6)*.

Appendix 3D: Results from Entropy Balancing the Baseline Estimation Sample

Table D1. First and Second Moments of Selected Covariates Before and After Entropy Balancing

Variable	No Extended Lockdowns – Before Entropy Balancing N = 73,432		No Extended Lockdowns – After Entropy Balancing N = 73,432		Extended Lockdowns N = 92,419	
	Mean	Variance	Mean	Variance	Mean	Variance
Extroversion (Normalised)	0.567	0.032	0.571	0.033	0.571	0.033
Emotional Stability (Normalised)	0.700	0.032	0.704	0.032	0.704	0.032
Agreeableness (Normalised)	0.730	0.024	0.740	0.022	0.740	0.022
Conscientiousness (Normalised)	0.687	0.024	0.689	0.029	0.689	0.029
Openness (Normalised)	0.532	0.031	0.541	0.031	0.541	0.031
Male	0.463	0.249	0.465	0.249	0.465	0.249
Age: 25-34	0.166	0.138	0.172	0.142	0.172	0.142
Age: 35-44	0.180	0.148	0.175	0.144	0.175	0.144
Age: 45-54	0.191	0.155	0.183	0.150	0.183	0.150
Age: 55-64	0.160	0.134	0.161	0.135	0.161	0.135
Age: 65 and over	0.177	0.146	0.182	0.1491	0.182	0.1491
Education Level: Year 12 or Above	0.725	0.199	0.774	0.175	0.774	0.175
Marital Status: De Facto Relationship	0.154	0.130	0.130	0.113	0.130	0.113
Marital Status: Separated	0.027	0.026	0.024	0.024	0.024	0.024
Marital Status:	0.072	0.066	0.056	0.053	0.056	0.053

Divorced						
Marital Status: Widowed	0.038	0.037	0.043	0.041	0.043	0.041
Marital Status: Never Married	0.189	0.153	0.203	0.162	0.203	0.162
Family Relationship: Couple with Child(ren) (<15 Years Old)	0.252	0.189	0.253	0.189	0.253	0.189
Family Relationship: Single Parent with Child(ren) (<15 Years Old)	0.035	0.034	0.024	0.024	0.024	0.024
Family Relationship: Single Parent without Child(ren) (<15 Years Old)	0.025	0.024	0.022	0.021	0.022	0.021
Family Relationship: Single Person (< 65 Years Old)	0.106	0.095	0.100	0.090	0.100	0.090
Family Relationship: Elderly Single Person	0.046	0.045	0.051	0.049	0.051	0.049
Family Relationship: Elderly Couple	0.119	0.104	0.119	0.105	0.119	0.105
Family Relationship: Dependent Student	0.036	0.034	0.049	0.046	0.049	0.046
Family Relationship: Non-Dependent Child (>15 Years Old)	0.054	0.052	0.060	0.056	0.060	0.056
Family Relationship: Other Family Member	0.017	0.017	0.015	0.015	0.015	0.015
Family Relationship: Unrelated to Household Members	0.009	0.009	0.010	0.010	0.010	0.010
Household Size: Children	0.584	1.002	0.551	0.897	0.551	0.897
Household Size: Adults	2.214	1.002	2.330	1.106	2.330	1.106
IRSAD: Decile 2	0.099	0.089	0.098	0.089	0.098	0.089

IRSAD: Decile 3	0.126	0.110	0.083	0.076	0.083	0.076
IRSAD: Decile 4	0.110	0.098	0.082	0.076	0.082	0.076
IRSAD: Decile 5	0.101	0.091	0.086	0.078	0.086	0.078
IRSAD: Decile 6	0.099	0.089	0.114	0.101	0.114	0.101
IRSAD: Decile 7	0.093	0.084	0.105	0.093	0.105	0.093
IRSAD: Decile 8	0.108	0.097	0.113	1.000	0.113	1.000
IRSAD: Decile 9	0.089	0.081	0.123	0.108	0.123	0.108
IRSAD: Decile 10	0.084	0.077	0.125	0.109	0.125	0.109
Dwelling: Semi/Terrace/Townhouse	0.055	0.052	0.075	0.069	0.075	0.069
Dwelling: Flat	0.076	0.070	0.122	0.107	0.122	0.107
Dwelling: Other	0.008	0.008	0.006	0.006	0.006	0.006
Remoteness Area: Inner Regional Australia	0.210	0.166	0.236	0.180	0.236	0.180
Remoteness Area: Outer Regional Australia	0.149	0.126	0.064	0.060	0.064	0.060
Remoteness Area: Remote or Very Remote Australia	0.029	0.028	0.001	0.001	0.001	0.001
Lag of Labour Force Status: Unemployed	0.034	0.033	0.029	0.028	0.029	0.028
Lag of Labour Force Status: Not Economically Active	0.312	0.215	0.302	0.211	0.302	0.211
Lag of Log of Real Household Income Per Capita	10.020	0.361	10.090	0.370	10.090	0.370
Lag of Smoker	0.187	0.152	0.157	0.132	0.157	0.132

Lag of Weekly Drinker	0.464	0.249	0.470	0.249	0.470	0.249
Lag of Self-Rated Health: Fair	0.144	0.123	0.123	0.108	0.123	0.108
Lag of Self-Rated Health: Good	0.383	0.236	0.349	0.227	0.349	0.227
Lag of Self-Rated Health: Very Good	0.345	0.226	0.381	0.236	0.381	0.236
Lag of Self-Rated Health: Excellent	0.096	0.087	0.121	0.106	0.121	0.106
Lag of Long-Term Health Condition	0.288	0.205	0.259	0.192	0.259	0.192
Lag of Social Support Index	54.100	103.400	54.920	100.500	54.920	100.500
Lag of Frequency of Social Interaction: Once or Twice Every Three Months	0.066	0.061	0.061	0.057	0.061	0.057
Lag of Frequency of Social Interaction: About Once a Month	0.124	0.109	0.119	0.105	0.119	0.105
Lag of Frequency of Social Interaction: Two or Three Times a Month	0.195	0.157	0.193	0.156	0.193	0.156
Lag of Frequency of Social Interaction: About Once a Week	0.312	0.215	0.322	0.218	0.322	0.218
Lag of Frequency of Social Interaction: Several Times a Week	0.214	0.168	0.223	0.173	0.223	0.173
Lag of Frequency of Social Interaction: Every Day	0.030	0.029	0.032	0.031	0.032	0.031
Lag of Self-Rated Financial Status: Poor	0.028	0.027	0.022	0.022	0.022	0.022

Lag of Self-Rated Financial Status: Getting Along	0.275	0.200	0.244	0.184	0.244	0.184
Lag of Self-Rated Financial Status: Reasonably Comfortable	0.537	0.249	0.537	0.249	0.537	0.249
Lag of Self-Rated Financial Status: Very Comfortable	0.141	0.121	0.172	0.144	0.172	0.144
Lag of Self-Rated Financial Status: Prosperous	0.012	0.012	0.019	0.019	0.019	0.019
Lag of Any Negative Event	0.401	0.241	0.383	0.236	0.383	0.236
Notes: All figures correct to three decimal places. Entropy balancing conducted with Stata user written package *ebalance* (Hainmueller and Xu, 2013).						

Appendix 3E: Additional Results Tables

Table E1. Effect of Extended Lockdown on Alternative Outcome Measures

Variable	(1) SF6D QoL	(2) Life Satisfaction	(3) K10 Score (Reversed)
	ATT (t-stat)	ATT (t-stat)	ATT (t-stat)
D2020 x 2020 Lockdown	-0.006 (-1.61)	-0.005 (-0.16)	-
D2020 x 2021 Lockdown	-0.008*** (-3.84)	-0.060** (-2.32)	-0.766*** (-3.42)
D2021 x 2021 Lockdown	-0.001 (-1.25)	-0.001 (-0.05)	-0.358*** (-3.36)
D2020 Aggregated ATT	-0.007*** (-2.59)	-0.032 (-1.26)	-
All Cohorts Aggregated ATT	-0.005*** (-2.58)	-0.022 (-1.23)	-0.562*** (-3.98)
N	161,055	164,788	77,887

Notes: ATTs correct to 3 decimal places, t-statistics to 2 decimal places. Statistical significance indicated by * at the 10%, ** at the 5%, and *** at the 1% level. Models 1 and 2 estimated using linear fixed effects regression, with Model 3 estimated as a fixed effects linear probability model with waves 7, 9, 11, 13, 15, 17, 19, and 21 data only. Estimation implemented with the *reghdfe* Stata command. Cluster-robust standard errors are clustered at the GCCSA level. Individual and GCCSA fixed effects are absorbed. All models include the interaction terms required for ETWFE as utilised in the baseline analysis with covariate adjustment. Results on the individual coefficients estimated for the personality traits and covariates alongside the cohort-time indicators are available on request.

Table E2. Fixed Effects Regression with OxCGRT Variables – No Moderating Effect

Variable	(1) No Deaths or Cases	(2) With Deaths and Cases
	Coefficient (t-stat)	Coefficient (t-stat)
OxCGRT Stringency	-0.034*** (-2.76)	-0.018*** (-2.59)
Extroversion	5.282*** (12.09)	5.275*** (12.00)
Emotional Stability	8.447*** (21.89)	8.455*** (21.65)
Agreeableness	1.402*** (3.70)	1.414*** (3.71)
Conscientiousness	1.257** (2.25)	1.245** (2.23)
Openness	0.938* (1.73)	0.934* (1.72)
State COVID-19 Deaths	-	-0.002** (-2.37)
State Covid-19 Cases	-	0.000 (0.69)
Covariates	Yes	Yes
Time Fixed Effects	Yes	Yes
GCCSA Fixed Effects	Yes	Yes
Entropy Balanced	No	No
N	187,074	187,045

Notes: ATTs correct to 3 decimal places, t-statistics to 2 decimal places. Statistical significance indicated by * at the 10%, ** at the 5%, and *** at the 1% level. Models estimated using fixed effects regression implemented with the *reghdfe* Stata command. Cluster-robust standard errors are clustered at the GCCSA level. Individual and GCCSA fixed effects are absorbed. For column 2, results on the individual coefficients estimated for the personality traits and covariates alongside the cohort-time indicators are available on request.

Table E3. Effect of Extended Lockdown with Removal of Observations Outside of Lockdown

Variable	(1) No Pre-Lockdown	(2) No Pre- or 4-weeks Post-Lockdown	(3) No Pre- or Post-Lockdown
	ATT (t-stat)	ATT (t-stat)	ATT (t-stat)
D2020 x 2020 Lockdown	-1.522*** (-3.46)	-1.532*** (-3.48)	-1.535*** (-3.64)
D2020 x 2021 Lockdown	-2.358*** (-5.32)	-2.366*** (-4.65)	-2.488*** (-5.16)
D2021 x 2021 Lockdown	-0.953*** (-3.52)	-1.018*** (-3.69)	-0.832*** (-2.66)
D2020 Aggregated ATT	-1.940*** (4.74)	-1.949*** (-4.35)	-2.011*** (-4.79)
All Cohorts Aggregated ATT	-1.611*** (-5.19)	-1.638*** (-4.91)	-1.618*** (-4.96)
N	163,878	163,586	163,014

Notes: ATTs correct to 3 decimal places, t-statistics to 2 decimal places. Statistical significance indicated by * at the 10%, ** at the 5%, and *** at the 1% level. Models 1 and 2 estimated using linear fixed effects regression, with Model 3 estimated as a fixed effects linear probability model with waves 7, 9, 11, 13, 15, 17, 19, and 21 data only. Estimation implemented with the *reghdfe* Stata command. Cluster-robust standard errors are clustered at the GCCSA level. Individual and GCCSA fixed effects are absorbed. All models include the interaction terms required for ETWFE as utilised in the baseline analysis with covariate adjustment. Results on the individual coefficients estimated for the personality traits and covariates alongside the cohort-time indicators are available on request. The ATTs were obtained using the methods shown in *Equations (7)* and *(8)* applied to the cohort-time specific ATTs.

Table E4. Moderating Effect of Personality with Removal of Observations Outside of Lockdown

Variables	(1) No Pre-Lockdown	(2) No Pre- or 4-weeks Post-Lockdown	(3) No Pre- or Post-Lockdown
	ATT (t-stat)	ATT (t-stat)	ATT (t-stat)
D2020 x 2020 Lockdown	-1.555*** (-3.71)	-1.569*** (-3.75)	-1.571*** (-3.94)
D2020 x 2021 Lockdown	-2.351*** (-5.49)	-2.363*** (-4.85)	-2.496*** (-5.35)
D2021 x 2021 Lockdown	-0.978*** (-3.53)	-1.037*** (-3.66)	-0.846*** (-2.64)
D2020 x 2020 Lockdown x Extroversion	-4.715*** (-4.49)	-5.064*** (-5.02)	-5.248*** (-5.37)
D2020 x 2020 Lockdown x Emotional Stability	5.344*** (7.90)	5.467*** (8.81)	5.593*** (8.75)
D2020 x 2020 Lockdown x Agreeableness	-4.385* (1.78)	-4.653* (-1.93)	-4.512** (-2.10)
D2020 x 2020 Lockdown x Conscientiousness	-0.065 (-0.04)	-0.075 (-0.05)	-0.483 (-0.35)
D2020 x 2020 Lockdown x Openness	2.740** (2.13)	2.797*** (2.49)	2.781*** (2.58)
D2020 x 2021 Lockdown x Extroversion	-2.805** (-2.51)	-3.313** (-2.29)	-3.033** (-2.46)
D2020 x 2021 Lockdown x Emotional Stability	4.090*** (3.49)	4.378*** (3.76)	5.264*** (4.77)
D2020 x 2021 Lockdown x Agreeableness	1.792 (0.69)	2.655 (1.03)	2.116 (0.72)
D2020 x 2021 Lockdown x Conscientiousness	-2.062 (-1.09)	-2.131 (-1.14)	-1.599 (-0.83)
D2020 x 2021 Lockdown x Openness	-0.940 (0.64)	1.258 (0.81)	1.621 (1.07)
D2021 x 2021 Lockdown x Extroversion	0.934 (0.47)	-0.823 (-0.44)	-1.245 (-0.94)
D2021 x 2021 Lockdown x Emotional Stability	0.393 (0.17)	0.784 (0.41)	1.134 (0.56)
D2021 x 2021 Lockdown x Agreeableness	2.330 (0.79)	0.075 (0.69)	-0.976 (-0.45)

D2021 x 2021 Lockdown x Conscientiousness	0.592 (0.31)	1.617 (0.51)	0.648 (0.85)
D2021 x 2021 Lockdown x Openness	-0.049 (-0.18)	0.729 (0.40)	0.903 (0.49)
N	163,878	163,586	163,014

Notes: ATTs correct to 3 decimal places, t-statistics to 2 decimal places. Statistical significance indicated by * at the 10%, ** at the 5%, and *** at the 1% level. Models 1 and 2 estimated using linear fixed effects regression, with Model 3 estimated as a fixed effects linear probability model with waves 7, 9, 11, 13, 15, 17, 19, and 21 data only. Estimation implemented with the *reghdfe* Stata command. Cluster-robust standard errors are clustered at the GCCSA level. Individual and GCCSA fixed effects are absorbed. Personality traits are demeaned by cohort-time mean when used for DDD estimates. All models include the interaction terms required for ETWFE as utilised in the baseline analysis with covariate adjustment. Results on the individual coefficients estimated for the personality traits and covariates alongside the cohort-time indicators are available on request.

Table E5. Aggregated Cohort ATTs by Personality Trait with Removal of Observations Outside of Lockdown

Cohort	(1) No Pre-Lockdown	(2) No Pre- or 4-weeks Post-Lockdown	(3) No Pre- or Post-Lockdown
	Aggregated ATT (t-stat)	Aggregated ATT (t-stat)	Aggregated ATT (t-stat)
D2020 Cohort	-1.953*** (-5.01)	-1.966*** (-4.63)	-2.033*** (-5.11)
All Cohorts	-1.628*** (-5.41)	-1.656*** (-5.14)	-1.637*** (-5.18)
D2020 Cohort: Extroversion	-3.760 (-3.89)	-4.098*** (-3.70)	-4.141*** (-4.08)
D2020 Cohort: Emotional Stability	4.712*** (7.03)	4.922*** (7.03)	5.428*** (7.67)
D2020 Cohort: Agreeableness	-1.296 (-0.61)	-0.999 (-0.47)	-1.198 (-0.52)
D2020 Cohort: Conscientiousness	-1.063 (-0.70)	-1.103 (-0.72)	01.021 (-0.72)
D2020 Cohort: Openness	2.164** (2.18)	2.028** (2.08)	2.201** (2.14)
All Cohorts: Extroversion	-2.820*** (-2.72)	-3.006*** (-2.80)	-3.176*** (-3.41)
All Cohorts: Emotional Stability	3.453*** (3.67)	3.543*** (3.80)	3.997*** (3.98)
All Cohorts: Agreeableness	-0.733 (-0.38)	-0.641 (-0.34)	-1.124 (-0.56)
All Cohorts: Conscientiousness	0.068 (0.04)	-0.196 (-0.11)	-0.464 (-0.25)
All Cohorts: Openness	1.639 (1.43)	1.595 (1.41)	1.769 (1.51)
N	163,878	163,586	163,014

Notes: ATTs correct to 3 decimal places, t-statistics to 2 decimal places. Statistical significance indicated by * at the 10%, ** at the 5%, and *** at the 1% level. The ATTs were obtained using the methods shown in *Equations (7)* and *(8)* applied to the cohort-time specific ATTs presented in Table E5.

Robustness Check 3: Removing Observations Outside of Lockdown

Tables E4 to E6 in Appendix 3E provide the results from this robustness check, in which we tested the assumptions of our identification strategy whereby all individuals interviewed in states which exposed extended lockdown were considered as treated. We firstly re-estimated our baseline models excluding individuals who returned their SCQ before the imposition of extended lockdown. We then tightened this restriction to also exclude individuals who returned their SCQ four weeks after extended lockdown ended (since the SF36 asks individuals to consider the last four weeks when answering the questionnaire). Finally, we excluded all individuals who returned their SCQ outside of the extended lockdown dates. The results indicated that our baseline results were robust to all three tests, providing evidence for the validity of our identification strategy utilising all observations on individuals within these states.

Table E6. The Effect of Extended Lockdown on Mental Health within Greater Capital Cities

Variable	(1)
	ATT (t-stat)
D2020 x 2020 Lockdown	-1.901*** (-8.39)
D2020 x 2021 Lockdown	-2.860*** (-12.31)
D2021 x 2021 Lockdown	-1.308*** (-6.53)
D2020 Aggregated ATT	-2.380*** (-13.43)
All Cohorts Aggregated ATT	-2.023**** (-12.56)
2021 Aggregated ATT	-2.084*** (-9.85)
N	104,825

Notes: ATTs correct to 3 decimal places, t-statistics to 2 decimal places. Statistical significance indicated by * at the 10%, ** at the 5%, and *** at the 1% level. The ATTs were obtained using the methods shown in *Equations (7)* and *(8)* applied to the cohort-time specific ATTs. The '2021 Aggregated ATT' represents the aggregated effect of extended lockdown in 2021 across Greater Melbourne, Greater Sydney, and ACT as calculated in Li *et al.* (2023).

Table E7. The Moderating Effect of Personality within Greater Capital Cities

Variables	(1)
	ATT (t-stat)
D2020 x 2020 Lockdown	-1.919*** (-8.59)
D2020 x 2021 Lockdown	-2.874*** (-12.99)
D2021 x 2021 Lockdown	-1.343*** (-6.61)
D2020 x 2020 Lockdown x Extroversion	-4.175*** (-5.77)
D2020 x 2020 Lockdown x Emotional Stability	5.567*** (6.74)
D2020 x 2020 Lockdown x Agreeableness	-0.848 (-0.51)
D2020 x 2020 Lockdown x Conscientiousness	-1.994 (-1.57)
D2020 x 2020 Lockdown x Openness	1.268 (1.13)
D2020 x 2021 Lockdown x Extroversion	-0.352 (-0.48)
D2020 x 2021 Lockdown x Emotional Stability	3.829*** (3.85)
D2020 x 2021 Lockdown x Agreeableness	0.792 (0.23)
D2020 x 2021 Lockdown x Conscientiousness	-1.652 (-0.59)
D2020 x 2021 Lockdown x Openness	2.731* (1.76)
D2021 x 2021 Lockdown x Extroversion	-2.380 (-1.31)
D2021 x 2021 Lockdown x Emotional Stability	3.474*** (3.54)
D2021 x 2021 Lockdown x Agreeableness	-0.475 (-0.13)

D2021 x 2021 Lockdown x Conscientiousness	0.617 (0.13)
D2021 x 2021 Lockdown x Openness	2.977 (1.63)
N	104,825

Notes: ATTs correct to 3 decimal places, t-statistics to 2 decimal places. Statistical significance indicated by * at the 10%, ** at the 5%, and *** at the 1% level. Models 1 and 2 estimated using linear fixed effects regression, with Model 3 estimated as a fixed effects linear probability model with waves 7, 9, 11, 13, 15, 17, 19, and 21 data only. Estimation implemented with the *reghdfe* Stata command. Cluster-robust standard errors are clustered at the GCCSA level. Individual and GCCSA fixed effects are absorbed. Personality traits are demeaned by cohort-time mean when used for DDD estimates. All models include the interaction terms required for ETWFE as utilised in the baseline analysis with covariate adjustment. Results on the individual coefficients estimated for the personality traits and covariates alongside the cohort-time indicators are available on request.

Table E8. Aggregated Cohort ATTs by Personality Trait within Greater Capital Cities

Cohort	(1)
	Aggregated ATT (t-stat)
D2020 Cohort	-2.397*** (-13.85)
All Cohorts	-2.045*** (-12.98)
D2020 Cohort: Extroversion	-2.263*** (-3.66)
D2020 Cohort: Emotional Stability	4.698*** (5.58)
D2020 Cohort: Agreeableness	-0.028 (-0.01)
D2020 Cohort: Conscientiousness	-1.823 (-0.91)
D2020 Cohort: Openness	2.000 (1.62)
All Cohorts: Extroversion	-2.303*** (-3.08)
All Cohorts: Emotional Stability	4.290*** (5.08)
All Cohorts: Agreeableness	-0.177 (-0.07)
All Cohorts: Conscientiousness	-1.010 (-0.38)
All Cohorts: Openness	2.325* (1.82)
N	104,825

Notes: ATTs correct to 3 decimal places, t-statistics to 2 decimal places. Statistical significance indicated by * at the 10%, ** at the 5%, and *** at the 1% level. The ATTs were obtained using the methods shown in *Equations (7)* and *(8)* applied to the cohort-time specific ATTs presented in E8.

Robustness Check 4: Greater Capital Cities

We restricted the sample to those individuals residing in the Greater Capital City regions of states and territories. Tables E7 to E9 in Appendix 3E provide the results. These indicated our findings were generally robust, albeit the magnitude of the effects on lockdown were somewhat larger in the Greater Capital City sample. This was not unexpected given the greater stringency of lockdowns couples with likely differences in environmental conditions such as dwelling size and outdoor space. Our estimated ATTs were somewhat smaller than those obtained by Li *et al.* (2023), however the authors did not allow for heterogeneity in ATT by cohort. Furthermore, it was not clear whether the authors correctly followed the ETWFE approach outlined by Wooldridge (2021) as they did not present specification equations indicating the necessary interaction terms required for ETWFE, nor make any mention of these when outlining their methodology.

The results regarding the moderating effects of the personality traits were also generally consistent with the baseline model. Two notable differences were that extroversion no longer significantly moderated the effect of 2021 lockdown in Greater Melbourne, whilst emotional stability now provided protection against the mental health effects of extended lockdown in 2021 for residents of Greater Sydney and ACT. This indicates that city-dwelling extroverts may have found it easier to adapt to lockdown conditions. City-dwellers may plausibly have more social connections and be more technologically literate, allowing them to maintain such connections more easily under lockdown. Further, the greater importance of emotional stability in moderating the effect of lockdown on mental health was for residents of Greater Sydney relative to the Rest of NSW may reflect the fact that residents of Greater Sydney were younger, and therefore likely to be less emotionally stable given emotional stability increases with age (Hale *et al.*, 2023).

Table E9. Baseline Model with No Covariate Adjustment using Sample of Individuals Used in Entropy Balancing

Variable	(1) No Covariate Adjustment
	ATT **(t-stat)**
D2020 x 2020 Lockdown	-1.616*** (-2.83)
D2020 x 2021 Lockdown	-2.399*** (-3.10)
D2021 x 2021 Lockdown	-0.981** (-2.00)
D2020 Cohort Aggregated ATT	-2.008*** (-3.02)
All Cohorts Aggregated ATT	-1.665*** (-3.41)
2021 Lockdown Aggregated ATT	-1.690*** (-3.42)
D2020 x T	Yes
D2021 x T	Yes
Personality	No
Covariates	No
Personality x D2020 x T	No
Covariates x D2020 x T	No
Time Fixed Effects	Yes
GCCSA Fixed Effects	Yes
Entropy Balanced	No
N	164,841

Notes: ATTs correct to 3 decimal places, t-statistics to 2 decimal places. Statistical significance indicated by * at the 10%, ** at the 5%, and *** at the 1% level. The estimated model is the same as in column 1 of Table 7.1, except we restrict the sample to those used in the entropy balancing approach when covariate adjustment was used (*i.e.*, column 2 of Table 7.1). Model estimated using fixed effects regression implemented with the *reghdfe* Stata command. Cluster-robust standard errors are clustered at the GCCSA level. Individual and GCCSA fixed effects are absorbed. Due to the number of interaction terms required for the covariates in the ETWFE method we do not report these results (available on request). The aggregated ATTs were obtained using the methods shown in *Equations (7)* and *(8)* applied to the cohort-time specific ATTs.

Table E10. Simple Two-Way Fixed Effects Model

Variable	(1) No Deaths or Cases	(2) With Deaths and Cases
	Coefficient (t-stat)	Coefficient (t-stat)
Extended Lockdown	-1.336*** (-3.22)	-1.261*** (-2.69)
Extroversion	5.242*** (12.03)	4.893*** (14.06)
Emotional Stability	8.448*** (21.91)	8.202*** (14.56)
Agreeableness	1.399*** (3.74)	1.356*** (3.81)
Conscientiousness	1.274*** (2.29)	1.427*** (2.53)
Openness	0.891* (1.67)	0.604 (1.15)
Age: 25 to 34	-1.209*** (-10.31)	-1.404*** (8.49)
Age: 35 to 44	-1.689*** (-7.16)	-1.813*** (-6.11)
Age: 45 to 54	-1.465*** (-3.62)	-1.721*** (-3.96)
Age: 55 to 54	-0.647*** (-3.62)	-0.899* (-1.82)
Age: 65 and over	1.051 (1.62)	0.901 (1.44)
Education Level: Year 12 or Above	0.332 (1.56)	0.506*** (2.88)
Marital Status: De Facto Relationship	0.190 (0.88)	0.316 (1.40)
Marital Status: Separated	-2.616*** (-8.92)	-2.252*** (-14.26)
Marital Status: Divorced	0.041 (0.11)	0.605* (1.98)
Marital Status: Widowed	-2.216*** (-3.04)	-1.927*** (-2.89)

Marital Status: Never Married	-0.907*** (-2.89)	-0.555 (-1.61)
Labour Force Status: Unemployed	-0.403** (-2.27)	-0.732*** (-3.69)
Labour Force Status: Not Economically Active	-0.942*** (-5.28)	-0.293 (-1.61)
Log of Real Household Income Per Capita	-0.035 (-0.32)	-0.053 (-0.47)
Smoker	-0.748*** (-7.25)	-0.754*** (-6.08)
Weekly Drinker	-0.674*** (-6.08)	-0.631*** (-4.42)
Self-Rated Health: Fair	5.966*** (28.66)	6.114*** (26.13)
Self-Rated Health: Good	10.820*** (41.01)	10.896*** (35.49)
Self-Rated Health: Very Good	14.149*** (56.97)	14.152*** (54.12)
Self-Rated Health: Excellent	16.252*** (57.43)	16.174*** (54.23)
Long-Term Health Condition	-1.408*** (-13.07)	-1.399*** (-14.28)
Social Support Index	0.492*** (37.02)	0.496*** (34.94)
Frequency of Social Interaction: Once or Twice Every Three Months	0.611*** (6.97)	0.664*** (8.05)
Frequency of Social Interaction: About Once a Month	0.859*** (6.19)	0.928*** (6.55)
Frequency of Social Interaction: Two or Three Times a Month	1.101*** (7.95)	1.088*** (6.04)
Frequency of Social Interaction: About Once a Week	1.272*** (9.18)	1.321*** (8.10)
Frequency of Social Interaction: Several Times a Week	1.656*** (12.41)	1.725*** (10.59)
Frequency of Social Interaction: Every Day	1.360*** (5.18)	1.224*** (4.05)

Self-Rated Financial Status: Poor	2.187*** (3.49)	1.942*** (2.57)
Self-Rated Financial Status: Getting Along	5.361*** (7.19)	5.212*** (6.53)
Self-Rated Financial Status: Reasonably Comfortable	7.143*** (9.61)	6.911*** (8.48)
Self-Rated Financial Status: Very Comfortable	7.888*** (11.05)	7.798*** (9.50)
Self-Rated Financial Status: Prosperous	8.254*** (8.16)	8.189*** (7.61)
Any Negative Event	-1.368*** (-20.56)	-1.357*** (-22.86)
Family Relationship: Couple with Child(ren) (<15 Years Old)	0.557*** (2.94)	0.703*** (3.71)
Family Relationship: Single Parent with Child(ren) (<15 Years Old)	0.716 (1.50)	0.462 (0.95)
Family Relationship: Single Parent without Child(ren) (<15 Years Old)	0.506 (1.08)	0.263 (0.86)
Family Relationship: Single Person (< 65 Years Old)	0.178 (0.43)	0.069 (0.17)
Family Relationship: Elderly Single Person	0.278 (0.41)	-0.375 (-0.42)
Family Relationship: Elderly Couple	-0.642* (-1.67)	-0.840* (-1.88)
Family Relationship: Dependent Student	1.103** (2.30)	1.142** (2.45)
Family Relationship: Non-Dependent Child (>15 Years Old)	0.982* (1.66)	0.927 (1.60)
Family Relationship: Other Family Member	0.461 (0.96)	0.181 (0.33)
Family Relationship: Unrelated to Household Members	0.152 (0.32)	-0.005 (-0.01)
Household Size: Children	-0.155*** (-3.02)	-0.216*** (4.82)
Household Size: Adults	-0.074 (-1.22)	-0.058 (-0.86)
IRSAD: Decile 2	0.312 (1.14)	0.378 (1.21)

IRSAD: Decile 3	0.615* (1.69)	0.628 (1.29)
IRSAD: Decile 4	0.033 (0.10)	0.259 (0.58)
IRSAD: Decile 5	0.401 (1.59)	0.490 (1.47)
IRSAD: Decile 6	-0.054 (-0.17)	0.038 (0.09)
IRSAD: Decile 7	0.194 (0.82)	0.222 (0.72)
IRSAD: Decile 8	0.149 (0.43)	0.137 (0.35)
IRSAD: Decile 9	0.466 (1.55)	0.505 (1.64)
IRSAD: Decile 10	0.126 (0.29)	0.078 (0.16)
Dwelling: Semi/Terrace/Townhouse	0.134 (0.64)	0.076 (0.40)
Dwelling: Flat	0.045 (0.29)	0.028 (0.15)
Dwelling: Other	-0.033 (-0.05)	-0.234 (-0.27)
Remoteness Area: Inner Regional Australia	0.037 (0.13)	0.300 (1.24)
Remoteness Area: Outer Regional Australia	-0.012 (-0.04)	0.130 (0.40)
Remoteness Area: Remote or Very Remote Australia	-0.025 (-0.04)	-0.528 (-0.49)
Time Fixed Effects	Yes	Yes
GCCSA Fixed Effects	Yes	Yes
Entropy Balanced	No	Yes
N	187,074	164,841

Notes: Coefficients correct to 3 decimal places, t-statistics to 2 decimal places. Statistical significance indicated by * at the 10%, ** at the 5%, and *** at the 1% level. Models estimated using fixed effects regression implemented with the *reghdfe* Stata command. Cluster-robust standard errors are clustered at the GCCSA level. Individual and GCCSA fixed effects are absorbed.

Robustness Check 5: *Two-Way Fixed Effects Estimation*

For our fifth robustness check, we estimated *Equation (1)* using a simple TWFE model. The results are provided in Table E14 in Appendix 3E. Column 1 provides the results using an unweighted sample and Column 2 the results when employing entropy weights. We found the estimated DD coefficients representing the effect of lockdown on MHI-5 score to be -1.261 and -1.336 respectively in the unweighted and weighted models. These estimates were somewhat smaller than the estimated aggregated ATT across all cohort found in the equivalent ETWFE models, suggesting that there may be some bias using the TWFE estimator from negative weights (Goodman-Bacon, 2021), which confirms the necessity of the ETWFE approach.

We now briefly discuss the associations between the covariates and MHI-5 found in the TWFE model presented in Table E14. Our expectations for these relationships were primarily based on studies on the socioeconomic determinants of mental health and studies which have previously estimated mental health models using the HILDA data (Morack *et al.*, 2013; Milner *et al.*, 2016; Ervin *et al.*, 2021; Li *et al.*, 2023; Yang and Zikos, 2023) and a systematic review on the determinants of mental health in Australia (Heinsch *et al.*, 2022).

Focussing on column 1 of Table E1, most of the estimated coefficients were in line with expectations. We found all five of the Big Five personality traits were positively associated with mental health, with emotional stability being the most important, followed by extroversion, agreeableness, conscientiousness, and finally openness. This is consistent with the literature (Malouff *et al.*, 2005; Kotov *et al.*, 2010; Hakulinen *et al.*, 2015; Strickhouser *et al.*, 2017; Lyon *et al.*, 2021).

Turning to the individual-level controls, we found evidence of the expected U-shaped relationship with mental health (Morack *et al.*, 2013), with increasingly negative coefficients estimated in each age category up to 45- to 54-year-olds, with the size of the negative coefficient reducing for the 55 to 64 age group, and then becoming non-significant for the oldest age group. Next, we found that relative to married individuals, those who were separated or widowed exhibited poorer mental health, as did those who were never married. With the exception of divorce not being negatively associated with mental health, these associations were in line with expectations (Ervin *et al.*, 2021). Next, we found the expected negative relationship between unemployment and mental health, and a smaller negative association between not economically active and mental health (Milner *et al.*, 2016)

With regards to health and health behaviours, we found the expected negative association between smoking and weekly drinking with mental health (Yang and Zikos, 2023), whilst those with a long-

term health condition also presented with poorer mental health (Morack *et al.*, 2013). Conversely, each increasing self-rated health category exhibited an increasingly large association with MHI-5 score, with self-rated health being the most significant predictor amongst all covariates. Again, this is consistent with the existing literature (Morack *et al.*, 2013). Similarly, increasing levels of self-rated financial status were strongly associated with higher mental health scores. The social support index and frequency of social interactions also exhibited strong positive relationships with mental health. This was consistent with evidence for the importance of social support to mental health (Milner *et al.*, 2016; Heinsch *et al.*, 2022). The experience of a negative life event in the past 12 months exhibited the expected negative association (Morack *et al.*, 2013).

In terms of household-related variables, we unexpectedly found household income to not be significantly positive associated with mental health, perhaps due to controlling for a range of other socioeconomic factors. Little differences were found between individuals by relationship status within a household, whilst number of children within the household was negatively associated with mental health. The type of dwelling did not appear to be a significant predictor of MHI-5 score, nor did the IRSAD decile in which the household was located. Finally, no differences were found at the remoteness area level, which may not be surprising given this was likely highly correlated with GCCSA which we controlled for through fixed effects.

The results with the entropy balanced weights were largely consistent. Thus, we generally found the expected relationships between the socioeconomic and demographic characteristics which we conditioned on to obtain our ATTs in the ETWFE models.

Appendix 3F: Comparison of Analytical Sample and Missing Observations

Table F1. Descriptive Statistics for Analytical Sample and Missing Observations

Variable	Analytical Sample		Missing Sample		Difference In Mean
	N	Mean	N	Mean	
MHI-5	187,074	73.813	53,445	71.522	2.290***
Extroversion (Normalised)	187,074	0.570	30,665	0.577	-0.007***
Emotional Stability (Normalised)	187,074	0.700	30,369	0.695	0.005***
Agreeableness (Normalised)	187,074	0.734	30,628	0.718	0.016***
Conscientiousness (Normalised)	187,074	0.685	30,404	0.658	0.028***
Openness (Normalised)	187,074	0.536	30,235	0.522	0.015***
Greater Sydney	187,074	0.156	82,464	0.186	-0.031***
Rest of NSW	187,074	0.134	82,464	0.124	0.010***
Greater Melbourne	187,074	0.176	82,464	0.177	-0.001
Rest of Victoria	187,074	0.071	82,464	0.082	-0.011***
Greater Brisbane	187,074	0.101	82,464	0.089	0.011***
Rest of Queensland	187,074	0.115	82,464	0.116	-0.001
Greater Adelaide	187,074	0.066	82,464	0.063	0.003***
Rest of SA	187,074	0.025	82,464	0.027	-0.002***
Greater Perth	187,074	0.076	82,464	0.063	0.012***
Rest of WA	187,074	0.019	82,464	0.019	-0.002***
NT	187,074	0.007	82,464	0.007	0.000
Tasmania	187,074	0.034	82,464	0.028	0.006***
ACT	187,074	0.022	82,464	0.018	0.004***
Male	187,074	0.464	82,481	0.493	-0.028***
Age: 15-24	187,074	0.134	82,481	0.271	-0.137***
Age: 25-34	187,074	0.168	82,481	0.198	-0.028***
Age: 35-44	187,074	0.173	82,481	0.142	0.032***
Age: 45-54	187,074	0.182	82,481	0.123	0.059***
Age: 55-64	187,074	0.157	82,481	0.103	0.054***
Age: 65 and over	187,074	0.183	82,481	0.163	0.020***
Education Level: Year 12 or Above	187,074	0.742	82,332	0.621	0.121***
Marital Status: Married	187,074	0.521	82,439	0.343	0.178***
Marital Status: De Facto Relationship	187,074	0.143	82,439	0.186	-0.043***
Marital Status: Separated	187,074	0.025	82,439	0.029	-0.003***
Marital Status: Divorced	187,074	0.063	82,439	0.055	0.008***
Marital Status: Widowed	187,074	0.043	82,439	0.060	-0.017***
Marital Status: Never Married	187,074	0.204	82,439	0.328	-0.123***
Labour Force Status: Employed	187,074	0.653	82,481	0.594	0.059***
Labour Force Status: Unemployed	187,074	0.031	82,481	0.057	-0.026***

Labour Force Status: Not Economically Active	187,074	0.316	82,481	0.349	-0.033***
Real Household Income Per Capita	187,074	29,100 AUD	76,636	25,907 AUD	3,192***
Smoker	187,074	0.171	52,369	0.220	-0.049***
Weekly Drinker	187,074	0.467	52,326	0.397	0.070***
Self-Rated Health: Poor	187,074	0.031	52,089	0.033	-0.002**
Self-Rated Health: Fair	187,074	0.138	52,089	0.143	-0.005***
Self-Rated Health: Good	187,074	0.365	52,089	0.347	0.019***
Self-Rated Health: Very Good	187,074	0.358	52,089	0.346	0.011***
Self-Rated Health: Excellent	187,074	0.107	52,089	0.130	0.112***
Long-Term Health Condition	187,074	0.285	82,389	0.287	-0.002
Social Support Index	187,074	54.357	48,317	53.588	0.769***
Frequency of Social Interaction: Less than Once Every 3 Months	187,074	0.059	50,232	0.063	-0.003***
Frequency of Social Interaction: Once or Twice Every Three Months	187,074	0.065	50,232	0.056	0.008***
Frequency of Social Interaction: About Once a Month	187,074	0.123	50,232	0.107	0.016***
Frequency of Social Interaction: Two or Three Times a Month	187,074	0.194	50,232	0.175	0.019***
Frequency of Social Interaction: About Once a Week	187,074	0.314	50,232	0.299	0.015***
Frequency of Social Interaction: Several Times a Week	187,074	0.214	50,232	0.240	-0.026***
Frequency of Social Interaction: Every Day	187,074	0.030	50,232	0.060	-0.030***
Self-Rated Financial Status: Very Poor	187,074	0.007	52,238	0.010	-0.003***
Self-Rated Financial Status: Poor	187,074	0.025	52,238	0.031	-0.006***
Self-Rated Financial Status: Getting Along	187,074	0.257	52,238	0.271	-0.014***
Self-Rated Financial Status: Reasonably Comfortable	187,074	0.534	52,238	0.485	0.048****

Self-Rated Financial Status: Very Comfortable	187,074	0.160	52,238	0.173	-0.013***
Self-Rated Financial Status: Prosperous	187,074	0.017	52,238	0.029	-0.012***
Any Negative Event	187,074	0.389	51,593	0.426	-0.028***
Family Relationship: Couple (<65 Years Old) Without Children (<15 Years Old)	187,074	0.293	82,480	0.243	0.050***
Family Relationship: Couple with Child(ren) (<15 Years Old)	187,074	0.247	82,480	0.194	0.053***
Family Relationship: Single Parent with Child(ren) (<15 Years Old)	187,074	0.029	82,480	0.035	-0.005***
Family Relationship: Single Parent without Child(ren) (<15 Years Old)	187,074	0.024	82,480	0.024	-0.000
Family Relationship: Single Person (< 65 Years Old)	187,074	0.104	82,480	0.113	-0.009***
Family Relationship: Elderly Single Person	187,074	0.052	82,480	0.063	-0.011***
Family Relationship: Elderly Couple	187,074	0.119	82,480	0.081	0.038***
Family Relationship: Dependent Student	187,074	0.047	82,480	0.112	-0.065***
Family Relationship: Non-Dependent Child (>15 Years Old)	187,074	0.058	82,480	0.069	-0.011***
Family Relationship: Other Family Member	187,074	0.017	82,480	0.033	-0.016***
Family Relationship: Unrelated to Household Members	187,074	0.010	82,480	0.032	-0.022***
Household Size: Children	187,074	0.562	82,481	0.577	-0.015***
Household Size: Adults	187,074	2.276	82,481	2.359	-0.082***
Index of Relative Social Advantage and Disadvantage (IRSAD)	187,074	5.562	82,435	5.336	0.323***
Dwelling: Separate House	187,074	0.822	82,412	0.776	0.046***
Dwelling: Semi/Terrace/Townhouse	187,074	0.067	82,412	0.076	-0.009***
Dwelling: Flat	187,074	0.104	82,412	0.133	-0.029***
Dwelling: Other	187,074	0.007	82,412	0.014	-0.077***
Remoteness Area:	187,074	0.659	82,435	0.648	0.011***

Major City of Australia					
Remoteness Area: Inner Regional Australia	187,074	0.225	82,435	0.220	0.005***
Remoteness Area: Outer Regional Australia	187,074	0.103	82,435	0.112	-0.009***
Remoteness Area: Remote or Very Remote Australia	187,074	0.014	82,435	0.021	-0.007***
Notes: Figures are correct to three decimal places. Statistical significance indicated by * at the 10%, ** at the 5%, and *** at the 1% level.					