

The effects of children's departure, financial development, and internet access on mental health and obesity: evidence from China

By

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ABSTRACT

The impact of a rapidly developing economy and dramatically changing social structure on the health and well-being of Chinese citizens has received increasing attention. In this thesis, I examine how key socioeconomic factors affect the physical and mental health of Chinese individuals. Specifically, I focus on three main areas: the impact of young leavers on depression, the effects of financial development on mental health, and the relationship between internet use and overweight/obesity.

In Chapter 2, I explore the impact of the departure of young family members on the mental health of the left-behind older household members. Using data from the 2011 and 2013 waves of the China Health and Retirement Longitudinal Study (CHARLS), my findings challenge the conventional belief that the departure of younger family members worsens the mental health of older adults. Instead, I discover that the mental health of those left behind improves following the departure of a member of the younger generation. This improvement in mental well-being can be attributed to the benefits associated with increased consumption and financial transfers, which outweigh the negative impact of losing household members. My study contributes to the existing literature by examining how broader family structure changes influence mental health outcomes.

In Chapter 3, I evaluate the extent to which local financial development influences the prevalence of depression in China. To assess the effects of financial development, I combine the CHARLS dataset covering the period from 2011 to 2018 with a unique set of city-level

financial development indicators, including key dimensions of financial depth, accessibility, and digitalisation. My analysis reveals a significant positive relationship between financial development and the mental health of the local population. Specifically, a one standard deviation increase in the ratio of a city's total bank and non-bank loans to its gross regional product (GRP) is associated with a 1.9 percentage-point reduction in the likelihood of exhibiting depressive symptoms. Further investigation suggests that financial development improves mental health by alleviating the financial constraints that individuals face.

In Chapter 4, I examine the relationship between Internet use and overweight/obesity in China, focusing on both children and adults. Drawing on data from the China Health and Nutrition Survey (CHNS) over the period 2004 to 2018, I investigate how Internet usage impacts weight gain. I find that there is a significant positive correlation between Internet use and the likelihood of being overweight or obese, especially among children. Adults (children) face a 1.8 (7.9) percentage point higher risk of being overweight than those who do not use the internet. This effect is especially pronounced in rural areas, where Internet penetration has grown rapidly. My analysis also highlights three key mechanisms through which Internet use contributes to weight gain: increased consumption of unhealthy foods, reduced physical activity due to prolonged sedentary behaviour, and sleep deprivation.

Chinese residents are facing an increasingly severe mental health crisis, while the growing epidemic of overweight /obesity issue also poses a significant threat to public health. I present three separate studies that offer new insights into the impact of young leavers, financial development, and Internet use on both mental and physical health outcomes. The findings from this thesis contribute empirical evidence that is crucial for informing policy interventions aimed at improving the overall well-being of the Chinese population.

DEDICATION

谨以本文献给我的父母，

感谢你们给予我探索世界的机会，以及无尽的爱与支持。

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And lastly, I want to thank myself for my perseverance. Persistence, after all, is the key to life!

Declaration

I declare that the work in this PhD thesis was carried out in accordance with the requirements of the University of Birmingham. The thesis has not been submitted for any other academic award. The work presented in this thesis is my own work except where indicated by specific references in the text.

SIGNED: Yibei Qu

DATE: 25th September 2024

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Chapter One

Introduction

China's rapid economic development and dramatic changes in social structure have a significant impact on residents' mental and physical health. The impact of socioeconomic factors on residents' health has become a key topic concerning national livelihoods. Additionally, China's unique traditions, such as filial piety (Hamnett, 2020; Tu, 2016) and the collectivist nature of society, combined with its distinctive social structure (Chan and Wei, 2021), have added layers of complexity to the study of the determinants of health outcomes. As a result, understanding the multifaceted effects of both economic and cultural factors on health in China is essential for shaping policies that address the evolving needs of its population.

1.1 Mental Health in China: A Growing Concern

Mental health problems have become an increasingly pressing issue in China, particularly among the elderly. With China's rapid economic transformation and modernisation over the last few decades, traditional family structures have been challenged. This transformation presents a profound impact on the mental health of older individuals. Depression, anxiety, and loneliness are prevalent among China's older population, with over 20% of older adults

suffering from mild to severe depressive symptoms (Cao and Zheng, 2023).

The elderly are more vulnerable due to their limited access to mental health services and social support. China's ageing population is growing rapidly, with over 200 million individuals aged 60 and above (Chen et al., 2022). This demographic shift poses substantial challenges for policymakers, healthcare providers, and researchers alike, as mental health issues often remain undiagnosed or untreated among the elderly due to stigma, limited healthcare access, and financial barriers. Therefore, identifying and addressing the factors that contribute to mental health challenges among this population is of critical importance (Chen et al., 2015; Guo et al., 2011).

At the micro level, several factors deeply influence the mental health of elderly individuals in China, as highlighted by research. These include personal health, demographic characteristics, and the availability of family and financial support, all of which interact to affect mental health. As health deteriorates, elderly individuals often face a loss of independence, which leads to increased reliance on others. This shift can raise feelings of loneliness, helplessness, and social isolation, which heighten the risk of anxiety and depression. Furthermore, the decline in physical capabilities of elderly individuals can severely limit their ability to engage in daily activities and intensify mental health challenges (Lauber et al., 2003; Takagi et al., 2013; Dour et al., 2014).

Demographic characteristics, such as age, gender, education level, and marital status, are also key factors in mental health outcomes. Older individuals, especially those over 75, are more prone to depression, largely because of physical limitations and shrinking social networks (Takagi et al., 2013). Women are more vulnerable to anxiety and depression in particular. This pattern is attributed to traditional social roles and a higher likelihood of being widowed (Gigantesco et al., 2019). Educational attainment also influences mental health; those with higher levels of education tend to experience better psychological well-being,

possibly owing to stronger social networks and greater financial security. Marital status is another critical factor. Elderly individuals who are widowed or divorced often face increased loneliness and social isolation, which raise their risk of mental health issues (Kessler and Essex, 1982). Financial stability is also important, especially in rural areas where pension coverage is often inadequate. Financial insecurity exacerbates mental distress, while those with steady financial support tend to have better mental health (Golberstein, 2015; Sperandei et al., 2023). In addition to personal factors, elderly individuals' interactions with family members and the broader social environment also influence their mental health. Family relationships are particularly important in the cultural context of China, where intergenerational support has traditionally played a central role in caring for older adults.

The literature suggests that various macro-level factors influence the mental health of elderly individuals in China. Firstly, economic factors, such as income level and unemployment rate, directly affect mental health. Low income or financial insecurity can lead to heightened stress, anxiety, and feelings of helplessness, which are strongly associated with mental health disorders such as depression (Waddell, 2006). Economic inequality further exacerbates these problems, as individuals with lower socioeconomic status may have limited access to mental health resources and support systems (Tennant, 2001).

Secondly, social factors, including urbanisation, social inequality, and the availability of social support systems, play a critical role. Rapid urbanisation can lead to social isolation, increased competition, and stress caused by the fast-paced environment. An unequal society, in which large segments of the population feel marginalised or deprived, fosters feelings of exclusion which are detrimental to mental health. A strong social support network, on the other hand, acts as a protective factor by providing emotional and psychological assistance in times of distress (Chan, 2013; Song, 2014).

Finally, cultural attitudes towards mental health also play a role, as the stigma of

mental illness in Chinese culture can prevent individuals from seeking help, which worsens their condition. Therefore, targeted policy interventions and strong social support mechanisms are essential for improving mental health outcomes at the macro level (McWilliams et al., 2004).

As mental health issues in China continue to rise, studies have explored various factors influencing mental well-being. However, significant gaps, from micro and macro perspectives, remain in the literature, which I attempt to fill in the first two empirical chapters of this thesis.

1.1.1 A Micro-Level Factor Affecting Mental Health: Young Leavers

In the previous section, I discussed a number of macro factors that affect mental health. In addition to the impact of an individual's health and characteristics, the influence of other factors cannot be ignored. This is especially important for the elderly. One of the most significant factors is the changing family structure, particularly the departure of members of the younger generations. Traditionally, multi-generational cohabitation was a common practice in China, with children living with their parents and grandparents and providing emotional and material support (Shin and Park, 2022).

The literature on the effects of changes in family structure on mental health highlights both positive and negative outcomes. The departure of younger family members can lead to feelings of isolation, loneliness, and abandonment in left-behind older adults (Scheffel and Zhang, 2019; Yi et al., 2019). These emotions can exacerbate depressive symptoms and anxiety, as the elderly often rely heavily on their children for emotional and practical support. On the other hand, other studies suggest that the departure of younger family members may reduce the care burden on older adults, thereby relieving stress and improving

their mental well-being. In particular, remittances from younger family members working in cities may help alleviate financial pressures on the elderly and indirectly contribute to better mental health outcomes (Böhme et al., 2015; Zhang and Guariglia, 2024).

Although there is a large body of research on the impact of children leaving home on the mental health of the left-behind elderly, significant gaps remain. Most studies have focused solely on children leaving, often overlooking the broader family structure, particularly the important roles played by other relatives, such as daughters-in-law and grandchildren, in providing care and emotional support. In addition, these studies have mostly concentrated on rural children migrating to other regions while neglecting cases of relocation within the same city. As the traditional multi-generational family structure collapses, the younger generation in cities also begins to leave home and live independently.

1.1.2 A Macro-Level Factor Affecting Mental Health: Financial Development

At the macro level, financial development may be a critical factor influencing the mental health outcomes of older adults. Particularly in China, the financial system remains poorly developed compared to those of advanced economies. While mental health issues have traditionally been linked to macro factors such as social isolation, inadequate healthcare, and poverty, the literature lacks a comprehensive study of how financial development affects mental health.

China's financial system poses remarkable challenges. Access to credit and financial services is limited, especially for individuals and small enterprises(Demirgüç-Kunt and Klapper, 2013). These constraints have a greater effect on middle-aged and elderly individuals who often face difficulties in securing loans or accessing credit to deal with emergencies (Liu

et al., 2024; Yang et al., 2020; Banerjee, 2011). Many people in this age group depend on limited incomes, and some face the burden of higher out-of-pocket healthcare costs because of incomplete coverage by the public healthcare system. In addition, China's underdeveloped pension system leaves many elderly individuals without adequate financial support in their later years. Although this problem affects the population broadly, it may be more acute in underdeveloped regions, such as rural areas, where the financial infrastructure is even weaker (Demirgüç-Kunt and Klapper, 2013).

The connection between financial constraints and mental health is well-documented. Numerous studies show that individuals experiencing financial insecurity are more prone to stress-related mental health issues, as financial uncertainty heightens stress and reduces their ability to cope with life's challenges (Lund et al., 2010). Consequently, in China, middle-aged and elderly individuals facing financial pressures are especially vulnerable to mental health problems. These factors highlight the urgent need to address financial development as a determinant of mental health.

Although there is growing research on the economic factors affecting mental health, such as investigations of how economic development improves life expectancy and reduces neonatal mortality, few studies have specifically explored the link between financial development and mental health. Previous studies, e.g. Hu et al. (2024) have primarily focused on how credit access affects mental health in developed countries such as the United States. However, by limiting their scope to credit access, these studies have overlooked the broader aspects of financial development and the unique economic and institutional context of countries such as China.

1.2 Overweight/Obesity as a Serious Health Issue in China: The Impact of Internet Use

Parallel to the mental health crisis, China is facing a growing epidemic of overweight /obesity, which poses a significant threat to public health. Overweight /obesity rates have risen sharply over the past few decades, transforming what was once a rare condition into a common health issue across all age groups. Overweight /obesity is associated with a range of chronic conditions, including type 2 diabetes, cardiovascular diseases, and osteoarthritis, all of which can significantly impact quality of life. The burden of these conditions is often compounded by the fact that many individuals, especially as they age, already face multiple health issues, making the management of obesity-related complications even more challenging. In addition, obesity not only affects physical health but also affects mental health, and many studies have shown that people with obesity are also more likely to experience mental disorders such as depression and anxiety (Preiss et al., 2013). Given the severity and complexity of the obesity problem, it is important to explore the factors contributing to the increase in overweight and obesity and potential solutions.

There are many reasons for the rising obesity rate in China. One significant factor is that the Internet has been well-developed in China. The Internet has already become an indispensable part of Chinese residents' daily lives, with almost a billion users and increasing penetration in both urban and rural areas. The Internet indeed serves many purposes, such as providing easier access to information and communication. On the other hand, it is worth noting that the Internet has led to alterations in residents' lifestyles, such as rises in sedentary behaviours (Suris et al., 2014; Tsitsika et al., 2016). Furthermore, in China, the traditional Chinese diet is mostly plant-based with vegetables, grains and low fats. However, the fast development of the Internet is deemed the product of China's remarkable economic growth, which facilitates diets based on animal fats, processed foods, and sugars (Guo et al., 2021).

These contexts emphasise the need to explore the relationship between Internet use and obesity, which also motivated my study. I aim to investigate the broader impact of Internet use on obesity in China. Existing studies on obesity have mainly focused on the effects of sedentary behaviours (e.g. excessive television viewing) on weight gain (Hancox and Poulton, 2006). However, the impact of Internet use still needs to be explored, especially in China. In developed countries, studies provide different results on the relationship between Internet use and obesity. Some studies find that Internet use is associated with weight gain due to sedentary behaviour (Kautiainen et al., 2005), while others find no significant association (Adachi-Mejia et al., 2007). In China, studies mainly focus on urban areas, while the impact of Internet use on obesity in rural populations and different age groups is understudied. In addition, many of the existing studies lack a thorough analysis of the mechanisms by which Internet use contributes to obesity. While some studies have explored the effects of Internet use on physical activity, sleep patterns, and unhealthy food consumption (Mineshita et al., 2021), none of them have analysed these mechanisms empirically. As a result, there are still significant gaps in developing an understanding of the broader and deeper impacts of internet use on obesity in different populations and settings (Suris et al., 2014; Tsitsika et al., 2016).

1.3 Structure and Contents of the Thesis

This thesis focuses on distinct yet interconnected aspects of mental and physical health in China. It explores how evolving economic conditions, social dynamics, and technological advancements shape health outcomes, contributing to a deeper understanding of the factors affecting mental and physical well-being in China. Firstly, I examine the effect of the departure of younger family members on the mental health of those left behind, particularly older adults in China. The primary suggestion is that younger members leaving improve

the mental health of left households. Secondly, I study the relationship between financial development and mental health. I find a significant positive relationship between financial development and the mental health of the local population. Finally, I examine how Internet usage impacts weight gain. The results show a significant positive correlation between Internet use and the likelihood of being overweight among Chinese residents. Overall, this thesis examines the impact of micro- and macro-factors on aspects of individuals' physical and mental health, thereby providing new insights into understanding China's public health challenges. Apart from this introduction, the rest of this thesis is divided into four chapters.

Chapter 2 focuses on the impact of young leavers on the mental health of the remaining family members in China. While existing literature has examined the effects of migration of children on left-behind parents, the findings are inconsistent. Some studies emphasise the negative psychological impact of the departure of young people, such as isolation and loneliness, while others suggest potential positive effects, like the reduction of caregiving burdens (Guo et al., 2009; Böhme et al., 2015). This paper contributes to the literature by expanding the scope of analysis beyond children to include other family members, such as daughters-in-law and grandchildren, within the Chinese multi-generational cultural context. Additionally, the study broadens the traditional focus on migration by capturing younger individuals who leave their families to establish independent households, even if they remain within the same community. This aspect of young adult mobility has been underexplored in the literature. It represents a significant gap in understanding the broader social and psychological impact of the departure of young household members on the well-being of the left-behind middle-aged and elderly family members. Using data from the China Health and Retirement Longitudinal Study (CHARLS), this study provides empirical evidence that the mental health of middle-aged and elderly individuals improves after the departure of family members. These findings have important policy implications.

Chapter 3 explores the relationship between financial development and mental health,

which focuses on how local financial development can alleviate depressive symptoms among middle-aged and elderly individuals. To this end, I link the CHARLS to a unique set of city-level financial development data. I use the Centre for Epidemiological Studies Depression (CESD) score to measure the respondent's mental health. Respondents with a score of 12 or more on CESD indicate that they can be considered depressed. I also employ a comprehensive set of indicators to measure financial development in three domains: depth, accessibility and digitalisation. This study fills a significant gap in the literature by being the first to investigate the effects of city-level financial development on the mental health of residents in China. The findings show that higher levels of financial development are significantly associated with a lower likelihood of depression. Moreover, the positive impact of financial development on mental health is found to be more pronounced among older individuals, those in poor physical health, rural residents, and individuals with low educational attainment. Those groups are more likely to face significant financing constraints. The study concludes that financial development improves mental health by easing these financing constraints. It highlights the critical role that access to credit and financial services plays in alleviating financial pressure, which positively affects mental health outcomes. These findings provide valuable policy recommendations, particularly for enhancing financial access in underdeveloped regions to support mental health improvements.

Chapter 4 explores the link between Internet use and obesity. I use the CHNS over the period 2004–2018 to assess the influence of Internet usage on the Chinese population's overweight and obesity and the mechanisms underpinning this relationship. Furthermore, a heterogeneity analysis is carried out, taking into account age variations in Internet usage among Chinese citizens and urban-rural inequalities. I find a significant positive correlation between Internet use and the likelihood of being overweight among Chinese residents. Next, based on the results of a subgroup analysis, I discover a substantial association between being overweight and using the Internet among men of all ages, including adults and children.

Additionally, the results vary between rural and urban populations. Among adults in rural areas, there is a significant correlation between Internet use and being overweight, whereas this relationship is not observed in urban areas. For children, the pattern is reversed, with the association being stronger in urban areas than in rural ones. Based on my mechanism analysis, the impact of internet use on body weight can be explained by several factors: insufficient sleep, lack of physical activity, and the intake of energy and fats. My results extend and complement previous studies on the impact of Internet use on the health and obesity of the Chinese population. In addition, it provides a basis for the Chinese government to formulate public health policies targeting the health care management of obese and overweight populations.

As the conclusion of this thesis, Chapter 5 briefly summarises the findings and discusses the policy implications of the findings and the inspiration for future research.

Chapter Two

Young Leavers and Mental Health

2.1 Introduction

Typical family structures in China are traditionally characterised by norms of multigenerational cohabitation, whereby children live with their parents and grandparents, with the younger generation assuming the main caregiving responsibilities (Hu and Peng, 2015; Zhang and Wu, 2021; Pang et al., 2020; Jankowiak, 2021). This pattern was prominent in the past, as evidenced by data showing that in 1990, around 70.3% of older adults aged 65 and above lived with their children. However, by 2010, this figure had dropped to 53.9%, and the 2020 census revealed a further decline, with only 39.69% of individuals aged 60 and above residing with their children(Wen, 2024). However, recent evidence suggests that more millennials are choosing to leave their original families due to employment, marriage or other reasons (McGranahan and Tacoli, 2006; Yan, 2016). A recent study found that Chinese millennials are exhibiting growing tendencies toward homeownership, driven by factors such as employment opportunities, marriage, and personal aspirations (Huang et al., 2021). This trend signals a departure from traditional norms of family cohabitation and caregiving in favour of more individualized living arrangements. This shift in family structure has led to an increasing

number of left-behind older people, with more than 50 million older people in rural China unaccompanied by younger family members (Zheng and Yang, 2016).

Understanding how changes in family structure affect the mental health of middle-aged and older adults is a significant issue for both health economists and policymakers. While a large body of literature suggests that this change often has negative consequences (e.g., Mosca and Barrett (2016); Scheffel and Zhang (2019)), the complex mechanisms behind this relationship have been understudied.[1] Moreover, much of the existing literature predominantly addresses the effects of younger generations leaving the household due to migration, often neglecting other factors such as marriage or family formation, which may exert a positive influence on the mental health of older adults. This paper revisits this issue by examining the impact of younger generations departing from households in broader contexts and the mechanisms.

Two perspectives offer contrasting conjectures on how the departure of younger generation members affects the mental health of those left behind. The first is the Social Support Theory (SST), which emphasises that emotional and material support from family members plays a key role in maintaining the mental health of middle-aged and older adults (Shin and Park, 2022). According to this theory, when the younger generation leaves the family, middle-aged and older adults left behind may lose important sources of social support, leading to increased loneliness and psychological stress (Guo et al., 2009; Rook and Charles, 2017). On the other hand, the departure of younger family members can reduce the caregiving responsibilities of older individuals. Zhang and Guariglia (2024) suggest that the elderly may substitute spending from their children for their consumption. Additionally, the departure of young leavers provides the elderly with more time and freedom to engage in social

[1]Despite the literature by Tse (2013) pointing out that remittances can alleviate the financial pressure of elderly parents, they do not fully compensate for the lack of daily care and emotional support for elderly parents. In contrast, Guo et al. (2009) andYi et al. (2019) argue that the financial security provided by remittances can, to some extent, ease the emotional strain caused by children's migration.

activities and develop personal interests, which can further enhance their mental health (Lee and Ishii-Kuntz, 1987; Böhme et al., 2015; Mazzuco, 2006).

To explore the channels through which the departure of younger generation members impacts the mental health of those left behind, I begin by developing a simple conceptual framework that uses utility as a proxy for mental health. In this framework, the utility (or mental health) of the elderly is decomposed into three components: (1) utility gained from personal consumption, (2) utility gained from children's consumption, and (3) non-pecuniary benefits from the number of household members, which increases with more family members in line with SST. The departure of young leavers would significantly alter these three components, and the overall effect on the elderly's utility depends on the relative magnitudes of these changes. This framework generates the baseline specification and guides the mechanism analysis in the empirical part of the paper.

To empirically assess the effect of young leavers on the mental health of left-behind elderly, I use data from the 2011 and 2013 waves of the CHARLS, which includes 12,165 individuals aged 45 and above from 6,514 households. This survey provides reliable measures of elderly mental health using the CESD-10 score, along with information about young leavers in the household. My empirical approach estimates the average treatment effect by comparing the average change in mental health between a treatment group (households with young leavers) and a control group (households without young leavers). My findings indicate that, on average, the mental health of remaining household members improved after the departure of young family members. I also evaluate the intensive margin, examining the effect of the number of young leavers, and find that the results are consistent with those for the extensive margin.

I recognize that my benchmark findings could be influenced by selection bias, wherein young-generation members make caregiving decisions based on the mental health status of

elderly family members. For example, when elderly individuals are in poor mental health, younger family members may choose to stay home to provide care, creating a positive self-selection bias. This results in a situation where families in the control group (those without young leavers) have a higher proportion of elderly members with poor mental health compared to those in the treatment group (those with young leavers). Consequently, this could lead to an overestimation of the positive effect of young leavers on elderly mental health. Conversely, negative self-selection bias may occur when elderly individuals with access to alternative social support (e.g., assistance from friends, neighbors, or extended family) are less reliant on young family members. In such cases, younger family members are more likely to leave, which could lead to an underestimation of the positive effect of young leavers on elderly mental health. For instance, an elderly individual who receives regular help from a neighbor might encourage their adult children to pursue opportunities outside the family home. This additional support network could buffer against feelings of isolation or neglect, thereby mitigating potential negative effects on mental health due to the absence of young family members. These contrasting forms of self-selection illustrate the complexity of disentangling the causal effect of young leavers on elderly mental health. To address this potential endogeneity, I apply Propensity Score Matching (PSM) to re-balance the data. I also remove confounding samples with extremely poor mental health from the control group and re-estimate my baseline specification. The corresponding results show that my benchmark positive correlation persists, with an even larger magnitude.

To further support my findings, I test several potential mechanisms based on my proposed conceptual framework by examining heterogeneity. First, I show that the positive effect observed in my benchmark analysis is diminished when the left-behind elderly live alone, as these elderly experience greater non-pecuniary loss when their children leave. Second, to verify the mechanism related to changes in personal consumption, I calculate the change in per capita consumption from 2011 to 2013. my results indicate that the positive

effect of young leavers is more pronounced for those with greater increases in consumption. This supports my conceptual framework, suggesting that the mental health of the left-behind elderly improves when they invest more in their well-being.

Additionally, I explore the heterogeneous effects based on the age of the young leavers and find that my baseline effect is more pronounced for those over 25 years old. This could be because these senior leavers are more likely to be financially independent. In contrast, leavers at the schooling age may rely more on transfers from their parents that reduce the left-behind members' consumption. Finally, I discuss the effect of inter-generation transfer. I show that if the young-generation members have more monetary feedback to the left-behind members after they depart from the household, the change in the elderly's mental health condition could be more positive.

This paper contributes to the extensive literature on the impact of young leavers on left-behind elderly (Dennerstein et al., 2002; Mitchell and Lovegreen, 2009). my study diverges from the majority of this research by finding a robustly positive average effect. I provide a detailed discussion of the mechanisms behind this contradiction, suggesting that the positive effects of increased consumption and altruism outweigh the negative impact of losing family members. This sheds light on the complex relationship between psychological outcomes, economic behaviours such as consumption, and the decision to move out of the family household. Furthermore, the heterogeneous effects observed across different household structures, age groups, and consumption groups highlight the potential for targeted policy tools to improve household health conditions. This is consistent with findings from other literature on heterogeneous effects on mental health (Zhang and Guariglia, 2024; Appleton et al., 2024).

My paper also contributes to the literature on the implications of changes in traditional family structures in China (Liu et al., 2007; Zhai et al., 2015; Poulin et al., 2014;

Cheng et al., 2015; Zhang, 2020). I demonstrate that the weakening of kinship ties in China, while often associated with negative outcomes, may have some positive effects for certain households, offering a more nuanced understanding than what is suggested by the existing literature. This opens up new avenues for research and policy discussions on how to best support the elderly population in a rapidly changing social landscape.

The remainder of the paper is organised as follows. Section 2.2 reviews the relevant literature. Section 2.3 develops the conceptual framework to guide my empirical analysis. Section 2.4 describes my data and presents some summary statistics. Section 2.5 shows my baseline specifications and estimation methods. Section 2.6 presents the results and discussion. Section 2.7 provides further analyses. Section 2.8 concludes and provides policy implications.

2.2 Literature Review

Changes in family structure, particularly the departure of children, whether due to independent living or other reasons, can have a profound impact on the elderly (Dennerstein et al., 2002; Mitchell and Lovegreen, 2009).

Western studies consider the effect of family structure shifts, primarily in relation to the "empty nest" phenomenon. The "empty nest" is a psychological syndrome experienced by parents when a child departs from the family home for the first time, for example, to attend college or live independently (Oliver, 1977; Smith, 2018). It is accompanied by feelings of sadness, loneliness and a sense of loss as parents readjust to their children's departure, in turn changing day-to-day routines and redefining their identities as parents (Mitchell and Lovegreen, 2009; Piper, 2021). Notably, empty nest syndrome has traditionally been characterised as a time of loneliness and emotional loss for parents, often leading to mental

health issues such as depression and anxiety (Mitchell and Lovegreen, 2009; Smith, 2018). However, in recent times, studies now indicate that the empty nest period often offers more systematic opportunities for growth in terms of increased marital satisfaction, or even the ability to make new friends, and personal growth in the absence of a child (Tracy et al., 2022).

In the context of Chinese society, the term "empty nesters" specifically refers to elderly individuals whose children no longer live with them (Zhang, 2020). Research in China indicates that the departure of children can negatively impact the psychological health of the elderly, especially among those who are widowed and in rural areas where economic and social support resources are limited (Liu et al., 2007; Zhai et al., 2015; Silverstein et al., 2006; Cheng et al., 2015). These individuals often experience heightened feelings of loneliness and depression. However, the impact is not uniformly negative. As Chinese society becomes more individualised and traditional family values evolve, some elderly individuals adapt well to the empty nest lifestyle, reporting higher subjective well-being and enjoying the independence and autonomy it offers (Poulin et al., 2014; Zhang, 2020). For those living with a spouse, the absence of children can sometimes strengthen marital relationships, particularly in urban areas with better economic conditions and more robust social support systems.

While studies on the mental health of empty nesters reveal psychological problems in older people due to the loss of daily companionship, these studies tend to overlook the impact of the younger generation's migratory behaviour itself. I will fill this gap in existing research by further exploring the impact of the younger generation's departure from home on the mental health of older adults.

Several studies specifically examine the impact of children leaving home on the mental health of older adults (Mosca and Barrett, 2016; Cheng et al., 2017). Most of these studies focus on migration, which is a significant factor contributing to the younger generation

leaving home. Consequently, the impact of migration on those left behind, particularly children and the elderly, is of increasing interest in the literature (Bhugra, 2004; Stillman et al., 2009; Graham et al., 2015). I review this literature hereafter.

2.2.1 Evidence from Countries Other than China

Some literature has focused on investigating how the family members' migration between different countries affects the mental health of those who remain. For instance, Antman (2010) examines the impact of adult children migrating from Mexico to the United States on the health of elderly parents left behind based on the data from the 2001 Mexican Health and Ageing Study (MHAS). She concludes that migration may negatively affect parents' mental health, which is induced by the long-term separation between parents and children and with symptoms such as psychological stress. The conclusions of the study are more based on static analysis of cross-sectional data, which may ignore the impact of the time dimension on the relationship between variables to a certain extent.

Mosca and Barrett (2016) extend this research to Ireland by using data from two waves of The Irish Longitudinal Study on Ageing (TILDA) conducted between 2009 and 2013. They analyze the short-term effects of adult children's migration on the mental health of elderly parents. To better identify the direct impact of migration on parents' mental health, they use fixed-effect models and control for various life events that occur between the two waves, such as bereavement, the onset of disease, retirement, and unemployment. This approach allows them to more accurately measure the short-term changes in parents' mental health, particularly in depressive symptoms and feelings of loneliness, as a result of their children's migration. Compared to Antman (2010)'s study, Mosca and Barrett (2016) research not only focuses on changes in mental health but also reveals the different roles gender plays in this process. They find that children's migration significantly increases

mothers' depressive symptoms and loneliness, while the effect on fathers is not significant. The authors explain the possible reasons for this finding as being that women are more likely to give and receive emotional support and base their relationships on emotional intimacy. In addition, marital bonds are more important to men's well-being than women's and suggest that while men are more likely to find intimate attachments in marriage, women can also find protection from emotional isolation in other intimate relationships. This provides a new gender perspective for understanding the impact of migration on parents left behind. However, as children of parents with poorer mental health may be less likely to be out of the home, the estimates in this paper are likely to be lower than the average impact on the population.

Böhme et al. (2015) use the Children and Elderly Left Behind (CELB) dataset collected from Moldova's National Labour Force Survey framework over the period 2011-2012 to examine the impact of international migration of adult children on the health of elderly parents left behind. Compared to the previous two studies, this paper is more rigorous in controlling for self-selected migration by adult children. By using a specific sampling frame and original survey data, the authors conduct detailed checks to ensure that the findings are not biased by the permanent migration of older adults and their families who are in particularly good health. In addition, this paper employs a strategy that includes two instrumental variables to deal with potential endogeneity issues. First, an exogenous source of variation in the likelihood of migration is used, namely network growth interactions between household characteristics, older adult characteristics and village-level migration networks. Second, a second instrumental variable, the presence or absence of military personnel in a locality prior to 1990, is used to capture the effect of attracting people to migrate to former Soviet countries (especially Russia). By these measures, the paper ensures the robustness of the results. Their research indicates that migration does not have a significant impact on mental health. However, since immigration from Moldova is mostly legal or low-risk, visiting

parents for at least a few weeks a year is possible and common. This conclusion may not be representative.

Abas et al. (2009) finds a positive impact when studying the effect of children's migration on the mental health of elderly parents left behind in rural Thailand. The study uses data collected between 2006 and 2007 from the Kanchanaburi Demographic Surveillance System, covering 1,147 parents aged 60 and older. In this study, child migration is defined as the child living outside the parents' district for at least three months. The researchers measure depressive symptoms using the Thai version of the EURO-D questionnaire. The results indicate that parents with all children migrating outside the district exhibit significantly lower levels of depression compared to those with only some or no migrating children. The authors explain this finding by suggesting that families able to support all children migrating likely possess greater economic and social resources, which enable them to better cope with the changes brought by migration. Furthermore, while migration reduces direct contact between children and parents, remittances and other forms of support actually improve the elderly's quality of life, thereby reducing their depressive symptoms. This study challenges the traditional view that child migration generally leads to depression and loneliness among elderly parents. Instead, in the context of Thailand, families with all children migrating tend to be economically better off and rely on other forms of social support, such as help from neighbours and remote communication, which help maintain the emotional well-being of the elderly.

2.2.2 Evidence from China

In contrast to studies in other countries, which mainly focus on international migration, research on Chinese migrants mostly looks at internal migration from rural to urban areas. This is because of China's uneven economic development and large-scale rural-to-urban

labour migration, which leaves many older people in rural areas (Kanbur and Zhang, 1999; Knight and Gunatilaka, 2010). Using data from the 2011 CHARLS survey, Tse (2013) studies the effect of adult children's migration on the mental health of older parents left behind in rural China. The study shows that children's migration harms the mental health of the elderly, causing memory decline and more signs of depression. The effect is stronger when daughters move away, as they usually play a key role in caring for their parents. Although remittances ease some financial pressure, they do not fully make up for the loss of direct care and emotional support. Overall, the author concludes that the migration of adult children greatly worsens the mental health of older parents by reducing both physical care and emotional support. Since this study uses cross-sectional data, it may not accurately show the cause-and-effect relationships or long-term changes in the variables.

Building on these findings, Xiang et al. (2016) look at the wider impact of rural-to-urban migration on left-behind parents in China, using data from the Rural-Urban Migration in China (RUMIC) survey collected between 2008 and 2009 across nine provinces. The study shows that when adult children move to urban areas, it significantly raises the risk of mental health problems for left-behind parents, especially in terms of depression and loneliness. These negative effects on mental health are worse in families with only one child. The authors say these problems mainly happen because the traditional family support systems are breaking down. Similarly, Huang et al. (2018), using data from the China Health and Nutrition Survey (CHNS) from 1997 to 2006, find that child migration makes the mental health of left-behind parents worse, especially for older women, elderly people, and those living in remote areas. The study shows a drop in life satisfaction among left-behind elderly parents, which links to the lack of community care services in rural areas, making feelings of loneliness and isolation worse. While both studies point out the weakening of traditional family support systems, they do not explore enough how other social support networks, like community or government services, might help lessen the mental health problems of

left-behind parents. Because of this, the overall usefulness of the findings might be limited.

Scheffel and Zhang (2019) also use CHARLS data from 2011 to 2013 to verify the negative impact of child migration on the emotional health of rural left-behind elderly parents. The authors support Tse (2013) view, noting that while remittances may ease some financial burdens, they fall short in addressing the emotional needs of the elderly, leading to more severe mental health issues. Bridges and Liu (2022) extend this analysis, exploring the heterogeneous effects of child migration on the mental health and well-being of left-behind parents in rural and urban areas. Using data from the 2011 wave of CHARLS, the study finds that rural parents experience more severe negative impacts on their mental health, including a decline in subjective well-being and worsening depressive symptoms. The authors suggest that the weakening of support networks plays a significant role in this deterioration of parental mental health. One limitation of this study is that, by focusing only on rural parents, it may overlook the broader context and nuances of mental health impacts in urban areas, where different support mechanisms may be in place. Additionally, due to the use of cross-sectional data, the study cannot establish causality or track how mental health changes over time, leaving open the question of whether the observed effects are persistent or temporary.

Unlike previous studies, Nikoloski et al. (2019) find no evidence that left-behind parenting is associated with worse mental health. Using data from the 2015 wave of the CHARLS, they examined the impact of rural-to-urban migration on the depressive symptoms of left-behind elderly parents and find no significant relationship. The authors also observed that among left-behind parents, greater financial or emotional support from children is linked to fewer depressive symptoms. Their findings suggest that family support plays a crucial role in alleviating depressive symptoms. Given the lack of a comprehensive pension system in rural China, family support remains the primary source of care for older adults. However, the study's findings do not establish a causal relationship.

Although most studies reveal the negative impact or the impact of child migration on the mental health of left-behind parents, some research also suggests potential positive effects, arguing that financial support can partially offset the emotional void. Guo et al. (2009), using data from a survey conducted in 2001 and followed up in 2003, study the emotional and mental health impact of adult-child migration on elderly parents left behind in rural areas of the Anhui Province. This study focuses on three key dimensions: financial support, instrumental support, and emotional well-being, measured by depression and life satisfaction. The results show that parents with migrant children receive significantly more financial support compared to parents without migrant children. This result is attributed to remittances sent by migrant children, which serve as compensation for their physical absence and inability to provide direct care. The study finds that parents with migrant children exhibit lower levels of depression two years later compared to the present. However, this study is limited to analysing only one province. Given the significant differences in economic development, living habits, and culture among China's provinces, the results may not fully reflect the situation at the national level.

Yi et al. (2019) examine the impact of population migration on the mental health of left-behind elderly parents in rural China using CHARLS data from 2011-2015. Using the New Economics of Labour Migration (NELM) theory, the researchers present two opposing impacts: the emotional stress of losing family members due to migration and the psychological benefits of remittances from mobile children. The authors estimate the impact of these factors on the mental health of older parents left behind. The results suggest that emotional stress caused by the migration of family members has a significant negative impact on the mental health of older adults. However, the psychological comfort provide by remittances tends to mitigate this negative impact, as remittances help to reduce the economic stress faced by families in less developed rural areas. The study concludes that, overall, the left-behind elderly may experience some psychological benefits from child migration, primarily

due to the economic security provided by remittances. However, the authors do not provide an empirical explanation for why increased remittances would improve the health of left-behind parents.

2.3 Conceptual Framework

This paper discusses the effect of the departure of members of the younger generation on the mental health of the people who remain in the household, which is conceptually ambiguous. On the one hand, according to SST, young family members play a key role in maintaining the mental health of middle-aged and elderly individuals (Shin and Park, 2022). Thus, when younger family members leave, those left behind may experience increased loneliness and physical strain due to reduced social support. Various studies, including Guo et al. (2009) and Rook and Charles (2017), have identified this negative effect. On the other hand, Zhang and Guariglia (2024) suggests that household per capita consumption increases as younger family members depart. This implies that the mental health of those left behind might improve due to higher consumption. Furthermore, upon the departure of young household members, the left-behind older household members will have more time and space to engage in social activities or develop personal interests, which in turn can improve their mental health (Lee and Ishii-Kuntz, 1987; Böhme et al., 2015; Mazzuco, 2006).

I further explore these mechanisms using a simple economic model of Equation (2.1). Without losing generality, I use utility to represent mental health, where higher utility implies better mental health. I assume that the utility of the older generation, denoted as U, is a function of their own consumption c, the consumption of the younger generation c_y, and the number of household members N. I assume that $u'(\cdot) > 0$ and $u''(\cdot) < 0$, implying that the utility of the older generation increases with both their own consumption and that of their

descendants. The underlying assumption is that the elderly are altruistic and care about the younger generation in their households (Logan and Spitze, 1995; Sparrow et al., 2021).[2] In the utility function, the parameter parameter $\alpha(\alpha > 0)$ represents the weight assigned to these two components of utility, with a higher α indicating that the older family members care more about the younger family members than themselves. I also include a punishment component χ, which is a decreasing function of the number of household members N, i.e., $\chi'(\cdot) < 0$. This suggests that a smaller household size is associated with lower utility, which is in line with the SST mentioned earlier.

$$U_o = u(c) + \alpha u(c_y) - \chi(N). \tag{2.1}$$

Budget Constraints and Optimisation

I now present the budget constraint for households with or without departing descendants. Let the wage of the older generation be denoted as ω_o. For older individuals living with their descendants, I assume that the younger generation does not have any income, meaning the elderly must cover both their consumption and that of their children. Therefore, the budget constraint is expressed in Equation (2.2), where the wage of the older generation is allocated for the consumption of both the older and younger generation members.

$$c_o + c_y \leq \omega_o. \tag{2.2}$$

For households with departing children, I assume, for simplicity, that the older members of the household no longer need to cover their children's consumption, as the departing children can support themselves with their own income, denoted as ω_y. Additionally, older household members may receive a transfer τ from their children. Accordingly, the bud-

[2]Such effect is more profound in China (Li et al., 2010).

get constraint for the older household members with departing children is represented by Equation (2.3).

$$c_o \leq \omega_o + \tau, \quad c_y \leq \omega_y - \tau. \tag{2.3}$$

In optimizing utility, I assume that older household members and individuals living with their children choose both c_o and c_y to maximize the utility function (Equation (2.1)), subject to the constraint in Equation (2.2). By contrast, those with departing children maximize utility by selecting only their consumption c_o, subject to the constraint in Equation (2.3). For illustration purposes, I assume that the utility function $u(\cdot)$ takes a logarithmic form. With straightforward derivations, the indirect utility functions, denoted as V, for households with and without departing children are represented in Equation (2.4), where Δ represents the number of departing younger generation members.

$$V = \log \frac{\omega_0}{1+\alpha} + \alpha \log \frac{\alpha\omega_0}{1+\alpha} - \chi(N). \tag{2.4a}$$

$$V = \log(\omega_0 + \tau) + \alpha \log(\omega_y - \tau) - \chi(N - \Delta). \tag{2.4b}$$

Equation (2.4a) for older household members without young leaver, and Equation (2.4b) for older household members with young leaver.

Potential Effect of Young Leaver

I now illustrate the potential effect of young family members leaving on the mental health of the older left-behind household members, using Equation (2.4). This effect can be decomposed into several components as follows:

Channel 1–Effect of losing household members: When members of the younger generation move out, Δ in Equation (2.4) becomes positive, indicating a larger punishment χ due

to the smaller household size. This effect decreases utility and, in turn, worsens the mental health of the older left-behind household members.

Channel 2–Effect of change in own consumption: The utility of the older left-behind household members stemming from their consumption is captured by the first component of Equation (2.4). The consumption without young leavers is $\frac{\omega_o}{1+\alpha}$, while with young leavers, it becomes $\omega_o + \tau$. The sign of the change in consumption after the departure of young-generation members depends on the net transfer τ. If there is no net transfer ($\tau = 0$) or a positive net transfer ($\tau > 0$), I have $\omega_o + \tau > \frac{\omega_o}{1+\alpha}$. This means the older left-behind household members could consume more after their children leave the household, potentially improving their mental health. However, if the net transfer is negative ($\tau < 0$), i.e. if the members of the departed younger generation members rely on their parents' support after leaving, the elderly's consumption may decrease, with $\omega_o + \tau < \frac{\omega_o}{1+\alpha}$. This could result in a decline in their mental health.

Channel 3–Effect of change in children's consumption: This is captured by the second component of Equation (2.4). The utility gain from children's consumption is $\alpha \log\left(\frac{\alpha\omega_o}{1+\alpha}\right)$ for those without young leavers and $\alpha \log(\omega_y - \tau)$ for those with young leavers. The comparison between these two terms depends on the young leaver's wage ω_y and the net transfer τ. If the young leaver's wage is sufficiently high after leaving, the utility for the elderly could increase, leading to better mental health. Conversely, if the wage is too low, the effect could be negative. The trade-offs between these effects determine the overall impact on mental health.

I will hereafter analyse how the departure of young members of the household affects the mental health of the remaining household members, together with possible mechanisms underpinning the association mentioned above.

2.4 Data and Descriptive Statistics

2.4.1 The CHARLS Data

I utilize data from the CHARLS, which gathers detailed information on individuals' mental health, as well as household and personal attributes. CHARLS is a longitudinal survey targeting the Chinese population aged 45 and older, along with their spouses. Conducted by Peking University, this survey aims to comprehend the health and ageing issues among the middle-aged and elderly population in China by monitoring changes in health status, economic conditions, social relationships, and quality of life over time. Zhao et al. (2014) compare the socioeconomic characteristics of the respondents with national census data and concluded that the sample broadly represents the population of China aged 45 and above.

The survey began in 2011, covering 28 provinces, 150 county-level units, and 10,026 households, involving 17,705 respondents. I use data from the 2011 and 2013 waves of the CHARLS.[3] To examine the impact of household member departures on the mental health of the remaining family members, I first select individuals who participated in both the 2011 and 2013 surveys. At this stage, I retain 8,842 households and 19,367 observations. Given that the CESD score is my main variable, I exclude 2,113 observations that did not report it. Since the age structure of household members is a crucial factor in my analysis, I also exclude 2,576 observations from 1,623 households that do not provide age information for some members. Additionally, I exclude 2,916 observations with missing values in my control variables. My final sample consists of 12,165 observations from 6,545 households for the subsequent empirical analysis. To deal with outliers, I winsorize the continuous variables "Income" at the upper and lower 1% quantiles.

[3]In the CHARLS 2013 survey, question CM003_W2_1 collected data on household member move-out details. However, the question was cancelled in subsequent surveys. Therefore, I did not use CHARLS data for 2015, 2018 and 2020.

2.4.2 Variable Construction

Mental Health Measurements

Along the main text, I measure mental health status through depressive symptoms; I assess it through the 10-item scale developed by the Centre for Epidemiologic Studies, commonly known as the CESD-10 scale (Andresen et al., 1994). A large body of literature has confirmed the validity of this index.[4]

The CESD-10 scale consists of 10 sub-measures, including eight depressive symptoms and two positive emotions, as follows: (1) feeling bothered, (2) being very irritable, (3) feeling fearful, (4) feeling anxious, (5) finding everything difficult, (6) feeling worthless, (7) feeling depressed, (8) feeling lonely, (9) feeling happy, and (10) feeling hopeful. Responses to each item are scored as: "rarely or none of the time" (1 point), "some or a little of the time" (2 points), "occasionally or a moderate amount of time" (3 points), or "most or all of the time" (4 points). In the CHARLS survey, respondents report the frequency of experiencing eight depressive symptoms and two positive emotions over the past week. I score these responses according to Radloff (1977)'s guidelines. The four frequencies answer the previous items are converted in score increasing from 0 to 3, from "Rarely or none of the time", "Some or a little of the time", "Occasionally or a modest amount of time", and "Most or all of the time". In the case of a negative item, such as feeling bothered, the total raw scores range from 0 (rarely) to 3 (often). In the case of a positive item, such as feeling happy, the total raw scores instead are descending from 3 (often) through 0 (rarely). By cumulating these scores across all items, the total score ranges from 0 to 30.

I use the total CESD score to measure individuals' mental health status, where a higher CESD score indicates more self-reported depressive symptoms and, therefore, a worse

[4]See, e.g., Chen and Mui (2014) and Zhou et al. (2021).

mental health condition. In addition to using the continuous CESD score, I are also interested in examining extreme cases of depression. Following Cheng and Chan (2005), individuals with a CESD score above 12 are classified as depressed. In the robustness checks, I will consider alternative measures of mental health, which will be introduced later.

Young Leavers

CHARLS provides direct information on household member changes. Specifically, in the 2013 wave of the survey, I can observe the number of household members who were present in 2011 but no longer part of the household by 2013 due to moving out, death, or other reasons. In this paper, I focus on the departure of this group of younger generations, including the respondent's children, grandchildren, and children-in-law. I evaluate both the extensive margin—whether there are any departing descendants—and the intensive margin—the number of departing descendants.

2.4.3 Descriptive Statistics

Table 2.1 presents descriptive statistics for the mental health variables measured based on my sample of 12,196 observations. The mean CESD score is 8.57, with a standard deviation (SD) of 6.26. This is consistent with previous studies that have employed the CESD scale in similar populations (Nikoloski et al., 2019). Furthermore, 27.88% of the sample meets the threshold for depression. This is consistent with previous literature, which reports that the prevalence of depressive symptoms among the elderly in China is 26% and 27.1%. (Li et al., 2019; Zhu et al., 2022). The summary statistics for the key independent variable, Departing Descendants, indicate that 7.8% of the sample has at least one departing descendant, while the average number of departing descendants is 0.188, with a standard deviation of 0.684 and a range from 0 to 9. These figures suggest that most families in the sample do not have

any departing descendants, but a small number of families have multiple departures.

Table 2.1 also shows the descriptive statistics for other variables used in this study, with the definitions of these variables provided in Table A.1. The sample's demographic details show an average age of 61.48 years, with a standard deviation of 9.76. The sample is almost evenly split by gender, with 49.4% being female, ensuring the findings apply to both men and women. In terms of marital status, 78.74% of the sample is married, while smaller percentages are never married (1.59%), widowed (17.91%), or divorced (1.76%). These numbers match the trends seen in similar studies of older adults in China, where marriage is common, and divorce rates among older groups are quite low (Gigantesco et al., 2019; Pan et al., 2022). Additionally, 60% of the respondents live in rural areas. Educational attainment among respondents is generally low: only 2% of the sample has a college degree or higher, and 10% have completed high school. This is consistent with previous literature, also based on the CHARLS, which reports low educational attainment among older adults, particularly in rural areas (Li et al., 2019; Gong et al., 2022).

Table 2.2 presents the composition of leavers by different age groups in my sample. In the 0-24 age group, the majority of leavers are grandchildren, accounting for 51.80%, followed by children at 39.35%, and spouses of children at 5.97%. Other family members represent only 2.88%. In contrast, in the 25+ age group, children remain the main group of leavers, accounting for 51.12% of the sample, but the significance of spouses of children increases markedly, representing 26.20%. Additionally, the proportion of leavers who are the respondents or their spouses is also notable, at 11.79%. Overall, children are the most common leavers across all age groups, while grandchildren play a significant role in the younger age groups (0-24). As age increases, the proportions of leavers who are spouses of children and the respondents or their spouses gradually rise. These data reflect the dynamic changes in family structure across different life stages.

2.5 Empirical Strategy

2.5.1 Baseline Specification

To empirically evaluate the effect of departing descendants on mental health, I follow the methodologies of Scheffel and Zhang (2019) and Zhang and Guariglia (2024) to estimate Equations (2.5) and (2.6). This specification leverages the panel variation in the data. The dependent variable, $MH_{i(p),t}$, represents the mental health of individual i in province p at year t. As previously mentioned, I use two types of measurements: the CESD score (denoted as $CESD_{i(p),t}$ after that) and an indicator for depression (denoted as $depression_{i(p),t}$ hereafter), which equals 1 if individual i has a CESD score above 12.

$$MH_{i(p),t} = \beta_0 + \beta_1 Young_move_{i(p),t} + Z_{i(p),t}\delta + \theta_i + \lambda_t + v_p \times \lambda_t + \varepsilon_{i(p),t}, \tag{2.5}$$

$$MH_{i(p),t} = \gamma_0 + \gamma_1 NumYoung_move_{i(p),t} + Z_{i(p),t}\delta + \theta_i + \lambda_t + v_p \times \lambda_t + \varepsilon_{i(p),t}. \tag{2.6}$$

Regarding the core explanatory variables, in Equation (2.5), $Young_move_{i(p),t}$ evaluates the extensive margin of young leavers. It is a dummy variable that takes the value of 1 if one or more young-generation members moved out of the household in 2013. By controlling for individual fixed effects θ_i and time fixed effects λ_t, Equation (2.5) follows a Difference-in-Differences (Diff-in-Diff) specification, where the treatment group consists of individuals with young leavers, and the control group consists of those without young leavers. Thus, $Young_move_{i(p),t} = 1$ for individuals in the treatment group during the treated year,[5] while the individual and year-fixed effects absorb the standalone indicators for the treatment group and the treated year. Correspondingly, the coefficient β_1 captures the average differential change in mental health between the treatment and control groups from 2011 to

[5]I focus on the young leavers who move out of the household in 2013. Thus, the treated year, in my case, would be the year 2013.

2013,[6] representing the average treatment effect on mental health due to the departure of young leavers.

In Equation (2.6), I replace the binary indicator $Young_move_{i(p),t}$ with a continuous measure of the number of departing descendants, $NumYoung_move_{i(p),t}$. This provides a more flexible Diff-in-Diff setup, where $NumYoung_move_{i(p),t} = 0$ for the control group and $NumYoung_move_{i(p),t} > 0$ for the treated group after the departure of young members. In this setup, the coefficient γ_1 now captures the intensive margin, measuring the change in mental health for each additional departing descendant, compared to those without any young leavers.

$Z_{i,t}$ represents the vector of control variables, which includes four sets of controls. First, following Lauber et al. (2003), Takagi et al. (2013), and Dour et al. (2014), I incorporate demographic characteristics such as age, gender, and marital status. Second, to account for individuals' economic and social status, I include log income level, an indicator for the highest education level, and unemployment status in my regressions. Third, in line with Daniel et al. (2004), Geoffroy et al. (2020), and Du et al. (2022), I consider the influence of lifestyle habits by controlling for alcohol and cigarette consumption, as well as social participation. Finally, I control for respondents' physical health, incorporating measures such as self-rated health, chronic diseases, and self-care ability. A more detailed discussion of the selection of control variables can be found in Appendix A.1.

Furthermore, I recognise that aggregate factors such as economic growth, government policy, and financial development[7] could significantly influence both mental health and the decision to leave the household (Osypuk et al., 2014; Wang and Granados, 2019; An et al., 2024). For example, social mobility may be higher in economically developed regions like

[6] Denote the dummy for the treated group as D_i and the dummy for the treated year as P_i, I could write $\beta_1 = \left[\mathbb{E}\left(MH_{i,t}|D_i = 1, P_t = 1\right) - \mathbb{E}\left(MH_{i,t}|D_i = 1, P_t = 0\right)\right] - \left[\mathbb{E}\left(MH_{i,t}|D_i = 0, P_t = 1\right) - \mathbb{E}\left(MH_{i,t}|D_i = 0, P_t = 0\right)\right]$.

[7] See the findings in Chapter 3 of this thesis.

Shanghai and Guangdong province, where younger generations are more likely to move out of the household. At the same time, these developed areas are often associated with higher living stress, which may negatively affect mental health (Chen et al., 2015; Yang and Chan, 2023). I are concerned that such regional differences could bias my subsequent estimation. Therefore, following Zhang and Guariglia (2024), I include an interactive fixed effect between province and time, i.e., $v_p \times v_t$, in Equations (2.5) and (2.6). This term absorbs all unobservable province-by-year variations, such as GDP per capita, GDP growth, business cycles, financial development, and changes in provincial policy. Additionally, I do not include v_p alone in the specification because the province fixed effect is already absorbed by the individual fixed effect θ_i. Finally, $\varepsilon_{i(p),t}$ trepresents the error term.

2.5.2 Estimation Methodology

I employ a Fixed Effects (FE) linear model to estimate Equation (2.1). Considering that my data is in a panel format, this method enables us to assess how changes in the independent variables over time influence individual mental health while effectively accounting for the confounding effects of unobserved, time-invariant individual traits. In addition to the fixed-effects models, I apply the correlated random-effects (CRE) Probit model when the dependent variable is binary, specifically for depression. The CRE Probit model, initially proposed by Mundlak (1978) and later adapted by Wooldridge (2019), is advantageous for panel data as it accommodates unobserved heterogeneity that may be correlated with observed covariates. This model parameterises the individual-specific error component as a function of the time averages of the time-varying explanatory variables, effectively controlling for any correlation between the unobserved heterogeneity and the explanatory variables.

2.6 Baseline Results

Equations (2.5) and (2.6) are estimated using a fixed-effects estimator. Table 2.3 displays the estimation results for the benchmark specification. Columns (1) and (2) show the estimates of Equation (5). In Column (1), where the CESD score measures mental health, the coefficient associated with $Young_move_{i(p),t}$ is negative and statistically significant, with a magnitude of approximately -0.58. This suggests that when one or more young-generation members leave the household, the CESD score for the older generation decreases by 0.58 units on average. Similarly, in Column (2), where the dependent variable is a dummy indicating depression, I find the coefficient associated with $Young_move_{i(p),t}$ is also negative and statistically significant. Specifically, the probability of being depressed decreases by 4.2 percentage points after the departure of a member of the younger generation.

Similar results are obtained when focusing on the number of departing descendants. The corresponding results are presented in Columns (3) and (4) of Table 2.3. I find that for each additional member of the younger generation moving out of the household, the CESD score for the older generation decreases by 0.244 units on average, and the probability of depression decreases by 2 percentage points.

These findings suggest that the departure of younger generation household members is associated with better mental health for those who remain. This improvement may be due to the reduction in economic burden or caregiving responsibilities that remaining members experience when younger members leave the household. Younger household members often depend on family resources for education and living expenses. Particularly in China, where multigenerational family structures are common, parents often shoulder the burden of supporting their children's education and daily needs. When younger members move out, the resulting alleviation of financial and caregiving stress allows remaining members to reallocate resources and time toward their well-being, which likely contributes to better mental health.

(Wheaton, 1990; Chen and Silverstein, 2000; Price et al., 2010). Additionally, the release of household resources after a member of the younger generation departs may enhance access to healthcare, social activities, and leisure of the left-behind household members, further supporting their mental health (Démurger and Wang, 2016; Secondi, 1997).

The estimates of the coefficients associated with the control variables shown in Table A.2 are consistent with the literature discussed in the previous section. The coefficient associated with the variable "Married" is statistically significant and negative both in the regressions for the CESD scores and the probability of depression, aligning with the well-documented protective effect of marriage on mental health (Kessler and Essex, 1982; Cutrona, 1996). Similarly, compared with poor self-rated health, both coefficients associated with good and fair self-rated health are negative and significant in the regression for the CESD scores, further supporting the established link between physical health and better mental well-being (Lorant et al., 2003). Additionally, the number of chronic diseases and self-care limitations are significantly and positively correlated with both CESD scores and the probability of depression, likely due to the increased stress and reduced quality of life associated with chronic conditions and disabilities. This finding reinforces existing literature that links chronic health issues and physical limitations to higher levels of depressive symptoms (Kuehner, 2017).

My findings suggest that the mental health of the left-behind household members improves when members of the younger generation move out of the household. This finding contradicts much of the existing literature on the effects of migration on household mental health (Mosca and Barrett, 2016; Scheffel and Zhang, 2019). For now, I refrain from fully interpreting the results, as a more detailed discussion will follow after conducting several specification and robustness checks.

2.7 Further Test

2.7.1 Robustness Check

Using a Different Estimator

In Table 2.4, I present results for the probability of suffering from depression obtained using a correlated random effects probit model. The results align with the baseline results.

Dropping leavers who passed away or left the household for reasons other than moving out

In my data, the specific reasons why young household members leave are not provided, except in cases where the young person passed away. Since the death of a young household member would likely lead to a deterioration in the mental health of those left behind, I check the robustness of my results by excluding these observations, as well as those where young people may have left for reasons unrelated to voluntary moving out, such as military service, incarceration, or long-term hospitalisation. These situations could also negatively impact the mental health of the elderly, and therefore, excluding them ensures that my results focus solely on the effects of voluntary departures.[8] The results, reported in Table 2.5, are consistent with the baseline findings. I can, therefore, conclude that cases of death or other involuntary departures did not drive the baseline results.

[8]In this way, the influence of mortality as a confounding factor would likely cause an underestimation of my baseline effect, as I generally find that the departure of young leavers improves mental health. Therefore, if the positive effect remains significant even when including the impact of mortality, I can expect the effect to be even stronger after removing the negative influence of mortality-related cases.

2.7.2 Propensity Score Matching (PSM)

The main challenge in assessing the causal relationship between the departure of members of the younger generation and the mental health of remaining household members is ensuring that observed changes in mental health are indeed caused by the departure and not by other factors. It is important to confirm that these changes would not have occurred if the younger generation had not left. However, in reality, I cannot observe this counterfactual situation, which means that I cannot simultaneously see the mental health of the same family with and without the younger generation leaving home. Therefore, even though I use panel estimators and incorporate a broad set of individual and household-specific factors into my models to reduce endogeneity concerns from omitted variable bias, my findings to date do not necessarily establish a causal relationship between the departure of offspring and changes in household mental health.

To better explore the association between the younger generation leaving home and the mental health of remaining family members, I use Propensity Score Matching (PSM) (Rosenbaum and Rubin, 1983). PSM approximates causal effects in counterfactual scenarios by simulating a randomised experiment, creating two comparable groups (treatment and control) based on observed characteristics. This approach significantly reduces confounding bias and mitigates selectivity bias, enabling a more accurate assessment of the impact of the younger generation's departure on the mental health of those left behind.

Methodology

Building on the general framework of PSM, I proceed to apply this approach in my analysis to estimate the causal effect of the younger generation's departure on the mental health of the remaining family members. First, I identify observed covariates and estimate propensity

scores. Specifically, I estimate a probit regression model to assess the probability of having the young generation leaving the household (treatment group). This probability is a function of all control variables in the baseline model evaluated in 2011. The fitted values from these regression models produce propensity scores that are used to identify households in the control group who have the same characteristics as the treatment group but no young leavers. This approach can form the basis of my matching.

Then, I use PSM methods to match treatment group households to the control group households with the closest propensity scores according to the principle of one-to-one nearest-neighbour matching. To ensure the accuracy of the matching, I allow the control group households to be matched to a different treatment group household multiple times during the matching process. In addition, I used a calliper matching method with a maximum threshold of 1% for the difference in propensity scores between treatment and control group households to ensure that the difference in propensity scores between matched pairs was within a reasonable range.

Third, following the approach of Zhang and Guariglia (2024), I define Average Treatment Effects on the Treated (ATT) as the expected difference in mental health change between the treatment and control groups over the period 2011 to 2013. The equation can be expressed as

$$ATT = \mathbb{E}(Y_1 - Y_2|D = 1) = \mathbb{E}(Y_1|D = 1) - \mathbb{E}(Y_0|D = 1), \tag{2.7}$$

where Y_1 represents the mental health status of the remaining household members after the younger members have departed (e.g., changes in CESD scores or depression). Y_0 would represent the counterfactual mental health status of the remaining household members if the younger members did not depart. $D = 1$ indicates that the household actually experienced the departure of younger members, constituting the treatment group. This is estimated

by analysing the observed changes in mental health among the households where younger members have left.

To calculate ATT, $\mathbb{E}(Y_1|D = 1)$ is estimated by analysing the observed changes in mental health among the households where younger members have left. $\mathbb{E}(Y_0|D = 1)$ is estimated using PSM to identify a control group of households that did not experience the departure of younger members but are otherwise similar to the treated group. The mental health status of this matched control group is used to approximate the counterfactual outcome. The ATT is then calculated as the difference between these two expected values, representing the average impact of the departure of younger household members on the mental health of the remaining members.

In the context of this study, ATT measures the average effect of the departure of younger household members on the mental health of those who remain, specifically for those households that have actually experienced this event. This effect is estimated by comparing the observed mental health outcomes (Y_1) with the counterfactual outcomes (Y_0) of what the mental health of the remaining members would have been if the younger members had not left.

Balancing Tests

In the instance of PSM conducted for my study, I rigorously performed balance tests to ensure that the matching process effectively equalised the covariate distributions between the treated and control groups. Despite the considerable size of my sample, t-tests consistently confirmed that my matching was successful in achieving statistical balance across all measured variables. Appendix A.2 provides the balancing tests conducted, illustrating the effectiveness of my matching process.

Results

I report the ATT for the departure of younger household members in Table 2.6. Column (1) presents the changes in CESD scores, and Column (2) presents the changes in the probability of experiencing depressive symptoms. The negative and statistically significant ATTs for changes in CESD scores and the probability of depressive symptoms suggest that households with members who leave show a marked reduction in depressive symptoms compared to similar households without such departures.

To further address this selection bias, in addition to using PSM to rebalance the data, I also removed the confounding sample of extremely poor mental health from the control group and re-estimated my baseline specification, the results of which are shown in Appendix A.3.

2.7.3 Mechanism

In the previous sections, I found robust evidence that the departure of members of the younger generation significantly improves the mental health of left-behind members of the older generation members. This finding contradicts studies such as Mosca and Barrett (2016) and Scheffel and Zhang (2019), which suggest that children's migration can negatively impact the elderly's sense of happiness. In this section, I propose some possible explanations for why my findings may be different from the literature. The results are consistent with my baseline results.

Recall that in my model, the change in mental health for left-behind members can be decomposed into three components: Channel 1 - the direct non-pecuniary loss from having fewer household members, Channel 2 - the change in the individual's consumption, and Channel 3 - the change in the children's consumption. While the first channel is expected to

affect the mental health of left-behind members negatively, the effects from the second and third channels could be positive. The overall positive impact of young leavers may occur when the second and third channels outweigh the first. I now provide supportive evidence for each channel.

Non-pecuniary Channel

I would expect Channel 1 to be stronger if there is only one left-behind household member who lives alone. I empirically demonstrate this by splitting the full sample into two subsamples: one for left-behind household members living alone after the departure and another for those with more than two members remaining in the household.[9] The results for these subsamples are presented in Columns (1) and (2) of Table 2.7. Consistent with my expectations, if the left-behind member lives alone after the descendants leave, the effect on their mental health is insignificant. In contrast, as shown in Column (2), if more than one left-behind member remains, my baseline findings hold, i.e. the departure of younger household members is associated with improved mental health of the left-behind household members.

Channels Through Consumption

In my theoretical model, the improvement in mental health could be explained by the mechanism that left-behind elderly members may increase their consumption, as expenses on the younger generation are reduced following their departure. This is supported by the findings of Zhang and Guariglia (2024). I replicate this result by regressing the log of average consumption per household member on my core explanatory variable $Young_move_{i(p),t}$ in

[9] I obtain the number of family members after the departure of young-generation members by deducting the number of departing members from the initial household size.

Column (1) of Table 2.8. The coefficient is positive, indicating that consumption increases after the young-generation members leave.

I connect this observation to mental health through the following steps. First, I calculate the change in consumption between 2011 and 2013, i.e. $\Delta C = C_{2013} - C_{2011}$. Next, I split the sample by the median of ΔC and re-estimate my baseline Equation (2.5) using these subsamples. I expect my baseline results to be more pronounced for the subsample with higher consumption growth. The corresponding results are presented in Columns (2) and (3) of Table 2.8. Compared to the regression with ΔC below its median, the effect of young leavers is more significant and has a larger magnitude in the regression with ΔC above its median. This supports my hypothesis regarding Channel 2 higher personal consumption after the departure of young leavers can marginally improve the mental health of left-behind elderly members.

Next, according to Channel 3 of my theoretical model, the change in young leavers' consumption can also impact the mental health of left-behind members. If the young leavers move out because they have secured a high-income job, the left-behind household members in the household may feel satisfied with the social achievements of their descendants, which could enhance their mental health. Conversely, if the young members leave the household without income and rely on parental transfers, the positive effect on mental health may be mitigated.

However, it is difficult to directly verify this channel using the CHARLS data, as it does not provide information about the young leavers' jobs or income. Therefore, I exploit the heterogeneity of young leavers' ages. Specifically, I examine the differential effect on the mental health of left-behind older family members when young leavers are below or above the age of 25. The intuition is that when children leave the household after the age of 25, it is more likely they are leaving for work with an income. However, for those below this

threshold, they may not yet have joined the labour force. In practice, I construct a dummy variable $Age25+$, which is equal to 1 for households with leavers aged 25 and above, and 0 otherwise and interact it with my core explanatory variable $Young_move_{i(p),t}$. I include this additional interaction term in my baseline Equation (2.5). The results are shown in Table 2.9. In Column (1), where I use the full sample, the coefficient associated with $Young_move_{i(p),t}$ is insignificant, but $Young_move_{i(p),t} \times Age25+$ is negative and statistically significant. This suggests that the CESD scores of left-behind household members are not affected by the departure of younger household members aged below 25 but are negatively affected by the departure of young people aged 25 and over. This result confirms my prediction: if young leavers move out without an income, such as for education, then the positive effect on the mental health of the left-behind older household members disappears.

Furthermore, in Columns (2) and (3) of Table 2.9, I follow the same approach as in Table 2.8 by splitting the sample based on the median of consumption growth between 2011 and 2013. I find that the coefficient associated with $Young_move_{i(p),t} \times Age25+$ is statistically significant and negative only for those households with higher consumption growth. This finding further supports my proposed mechanism: when young leavers move out and can support themselves with their income, the left-behind elderly can reallocate spending from their children to their consumption, which significantly improves their mental health.

The Effect of Transfer

Finally, as discussed in the theoretical model, intergenerational transfers between the left-behind and departing members are a key factor in determining the change in the consumption of left-behind household members. The consumption of the left-behind members increases after the departure of young leavers if the net transfer, defined as the difference between

transfers sent and received, is non-negative. To clarify, the net transfer (NT) refers to the amount of money the older household members receive from the younger members minus the amount they send. To verify this mechanism, following Hu et al. (2022), I calculate the net transfer as $NT = \tau_y - \tau_o$, where NT represents the net transfer, τ_y is the transfer from the young-generation member to the older-generation member, and τ_o is the transfer in the opposite direction. I then compute the change in net transfer as $\Delta NT = NT_{2013} - NT_{2011}$.[10] A positive ΔNT indicates that the elderly received more monetary resources from their descendants in 2013. Figure 2.1 shows the distribution of this variable, illustrating two distinct scenarios: part of the sample experienced an increase in net transfers between 2011 and 2013, while the rest saw a negative change.

To test the effect of net transfers, I split the sample into two groups: households with decreasing net transfers and households with non-decreasing net transfers and estimate Equation (2.5) for each of these sub-samples. Table 2.10 presents the results. In Column (1), I present the results for the subsample with decreasing net transfers ($\Delta NT < 0$). The estimated effect is insignificant, although the sign remains negative. In Column (2), I present the estimates of Equation (2.5) for the subsample with increasing net transfers ($\Delta NT \geq 0$), the coefficient is significantly negative, indicating that the CESD score of the left-behind elderly decreases following the departure of young leavers. These results support my proposed mechanism, suggesting that the positive effect of young leavers on the mental health of the remaining household members is more pronounced in the presence of net transfer to the left-behind elderly.

[10] In Section 2.4, I showed that the change in elderly's consumption is a function of net transfer (τ in Equation (2.4)). For the empirical analysis in this section, I use the change of the net transfer, i.e. ΔNT. I claim that these two measurements essentially present the same insights. This is because, in the theoretical model, I assume the monetary transfer from the old-generation member to the young-generation member is 0 before the departure of descendants. However, this number could be non-zero in the empirical data. Therefore, I use the first-order difference in my empirical analyses.

Discussion

I now revisit the question raised earlier: why does the positive effect of young leavers on the mental health of left-behind elderly members, as identified in my study, contradict the findings of Mosca and Barrett (2016) and Scheffel and Zhang (2019)? In studies examining the impact of descendants migrating to other cities or focusing on empty-nest elderly, the non-pecuniary burden (or emotional cost) of young leavers Channel 1 is often significant and tends to dominate the overall effect. However, these studies often use inter-city migration to represent young leavers, which may overlook cases where younger family members move out of the household but remain within the same city. For instance, young members might move out because they buy a new house nearby or get married. In these cases, the emotional cost to the elderly is relatively small. At the same time, the positive effects from increased consumption Channel 2 and financial transfers Channel 3 may outweigh the negative impact on their mental health.

My paper addresses this issue by directly identifying young leavers through survey data, which indicates whether younger generation members have moved out of the household, regardless of the reason or their destination. By including all such cases, I show that the departure of young leavers generally has a positive effect on the mental health of left-behind elderly members. This positive effect is likely driven by the fact that the benefits from increased consumption and financial transfers outweigh the emotional cost of losing household members.

2.8 Conclusion

This paper uses data from the 2011 and 2013 waves of the CHARLS to explore how the departure of members of the younger generation affects the mental health of those who

remain in the household. My analysis shows that the mental health of remaining household members tends to improve after younger family members leave. Furthermore, based on my development of a simple conceptual framework and through a series of heterogeneity analyses, I find that this positive effect may be due to the fact that the departure of younger family members reduces the financial burden of older people. Left-behind family members are able to increase their consumption, and younger family members tend to provide financial support in the form of remittances to left-behind family members when they leave the household, thus offsetting the emotional loss that may be associated with the departure of younger family members.

My study has a few limitations. First, due to data unavailability, I can only analyze the impact on the mental health of the remaining family members whose younger generation left between 2011 and 2013. This limitation restricts my ability to capture the long-term effects of this phenomenon fully. Nevertheless, by capturing the impact of changes in family structure within a relatively short timeframe, my study provides the government with valuable information for early intervention.

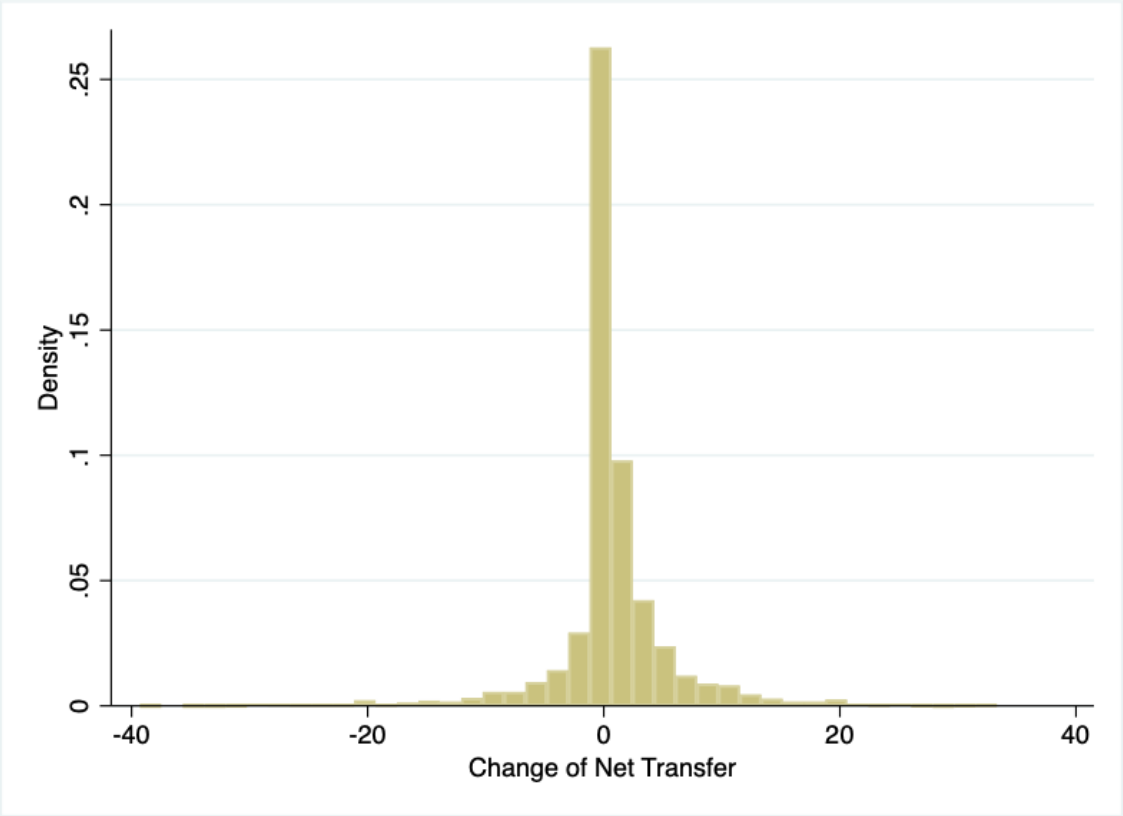
Second, although I employ panel data techniques, effectively controlling for factors that are unobserved and constant over time, these methods do not eliminate all potential confounders. Some variables that I cannot observe or quantify may affect both the decision of children to leave and the mental health of the remaining family members. These unobserved factors may include emotional connections between family members, decision-making dynamics within the family, or other social factors that may affect children's leaving home and family mental health. Thus, while my analyses provide valuable insights, I cannot fully conclude that the results are causally related. However, my robustness analysis using the PSM method shows that my conclusions are still reliable, addressing bias attributable to confounding and selection bias, which adds a certain degree of credibility to my research.

My results show that the departure of the younger generation has a positive impact on the mental health of remaining family members in the short term, which provides an important window for government policy intervention. To fully utilize this short-term positive effect, the government should take some specific measures. The government can encourage family members to maintain close contact with the left-behind elderly regularly in the early stage of departure and encourage and subsidize the use of convenient communication technologies such as video calls or social media. This continuous contact can help consolidate the positive psychological state of the elderly after their children leave and reduce long-term loneliness.

I also find that the departure of the newly independent young generation from the family has the most significant impact on the mental health of the remaining household members. In response to this result, the government can promote and support policies for young people to live independently, such as providing more affordable housing and employment opportunities. These measures will not only help young people achieve economic independence faster but also help further enhance left-behind family members' mental health. In addition, for independent young people, the government can promote and support work-life balance policies to ensure that they can still have time and energy to stay connected with their families during their busy careers. Such policies will indirectly support the mental health of left-behind family members.

Figures and Tables for Chapter 2

Figure 2.1: Distribution of the change of net transfers (ΔNT)



Note: The data is based on my main regression sample where respondents were aged 45 and above in both waves of the survey, and households participated in both waves of the survey.
Source: Authors' calculations based on the CHARLS.

Table 2.1: Descriptive statistics for all variables

VARIABLES	Mean	SD	Min	Max
Mental Health				
CESD	8.5710	6.2637	0.0000	30.0000
Depression	0.2788	0.4484	0.0000	1.0000
Departing Descendants				
Has Departing Descendants or not	0.078	0.459	0	1
Number Departing Descendants	0.1880	0.6841	0	9
Control Variables				
Age	61.4770	9.7579	45.0000	96.0000
Gender	0.4940	0.5000	0.0000	1.0000
Married	0.7874	0.4092	0.0000	1.0000
Never married	0.0159	0.1251	0.0000	1.0000
Widowed	0.1791	0.3834	0.0000	1.0000
Divorced	0.0176	0.1316	0.0000	1.0000
Illiterate	0.2721	0.4450	0.0000	1.0000
Elementary	0.4159	0.4929	0.0000	1.0000
Middle school	0.1913	0.3933	0.0000	1.0000
High school	0.0999	0.2998	0.0000	1.0000
College	0.0209	0.1431	0.0000	1.0000
Social	0.5541	0.4971	0.0000	1.0000
Smoke_now	0.3452	0.4755	0.0000	1.0000
Drink_now	0.3331	0.4713	0.0000	1.0000
Chronics	1.4336	1.4233	0.0000	9.0000

Continued on next page

Table 2.1 – continued from previous page

VARIABLES	Mean	SD	Min	Max
Limitation	0.6692	1.5114	0.0000	11.0000
Income	9.1850	1.3085	0.0000	12.3458
Work	0.6562	0.4750	0.0000	1.0000
Good health	0.2959	0.4565	0.0000	1.0000
Fair health	0.6232	0.4846	0.0000	1.0000
Bad health	0.0808	0.2726	0.0000	1.0000

Note: The descriptive statistics for all variables are derived from the sample used to estimate Equation (2.1) *in the main results. The total number of observations is 12,165.*

Table 2.2: Leavers by age group

Age Group	**Role**	**Number**	**Percentage (%)**
0-24	Child	547	39.35
	Spouse of child	83	5.97
	Grandchild	720	51.79
	Other	40	2.87
	Total	**1390**	**100**
25+	Child	798	51.12
	Spouse of child	409	26.20
	Grandchild	19	1.22
	Mother/mother-in-law	73	4.68
	Father/father-in-law	36	2.31
	Respondent/spouse	184	11.79
	Other	42	2.69
	Total	**1561**	**100**

Note: The data is based on my main regression sample where respondents were aged 45 and above in both waves of the survey, and households participated in both waves of the survey and provided age information for every household member.

Source: Authors' calculations based on the CHARLS.

Table 2.3: Baseline results

VARIABLES	**(1)** **CESD**	**(2)** **Depression**	**(3)** **CESD**	**(4)** **Depression**
Young move	-0.580***	-0.042**		
	(0.205)	(0.017)		
Number of Young moves			-0.244***	-0.020***
			(0.088)	(0.007)
Control variables	Yes	Yes	Yes	Yes
Observations	12,165	12,165	12,165	12,165
Number of id	6,514	6,514	6,514	6,514

*Notes: The table reports the estimates of the baseline model. All models are estimated using a fixed-effects linear estimator. The dependent variable in Columns (1,3) is the CESD score, and in Columns (2,4), it is the probability of having depression. Data from the 2011 and 2013 waves of the CHARLS were used in estimation. Standard errors clustered at the household level are in parentheses. Time dummies and the interactions between provincial and time dummies are included in all models, but their coefficients are not reported for brevity. The definitions of all variables are provided in Table A.1. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

Table 2.4: Baseline results; correlated random-effects probit estimates

VARIABLES	**(1)** **Depression**	**(2)** **Depression**
Young move	-0.028**	
	(0.017)	
Number of Young moves		-0.013***
		(0.009)
Control variables	Yes	Yes
Observations	12,165	12,165
Number of id	6,514	6,514

*Notes: The table reports the marginal effects obtained using a correlated random effects probit estimator. The dependent variable in all Columns is the probability of having depression. Data from the 2011 and 2013 waves of the CHARLS were used in estimation. Standard errors clustered at the household level are in parentheses. The means of time-varying variables are included in all models, but their coefficients/marginal effects are not reported for brevity. Time dummies and the interactions between provincial and time dummies are included in all models, but their coefficients are not reported for brevity. The definitions of all variables are provided in Table A.1. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

Table 2.5: Effect of young leavers on mental health outcomes differentiating leavers by age; dropping leavers who passed away or left for "other" reasons

VARIABLES	**(1)** **CESD**	**(2)** **Depression**	**(3)** **CESD**	**(4)** **Depression**
Young move	-0.602***	-0.046**		
	(0.232)	(0.014)		
Number of Young moves			-0.256***	-0.032***
			(0.067)	(0.006)
Control variables	Yes	Yes	Yes	Yes
Observations	11,327	11,327	11,327	11,327
Number of id	6,228	6,228	6,228	6,228

*Notes: The table reports the estimates of the baseline model dropping leavers who passed away or left for "other" reasons. All models were estimated using a fixed-effects linear estimator. The dependent variable in Columns (1) and (3) is the CESD score, and in Columns (2) and (4), it is the probability of having depression. Data from the 2011 and 2013 waves of the CHARLS were used in estimation. Standard errors clustered at the household level are in parentheses. Time dummies and the interactions between provincial and time dummies are included in all models, but their coefficients are not reported for brevity. The definitions of all variables are provided in Table A.1. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

Table 2.6: Average treatment effects on the treated (ATTs)

	(1)	**(2)**
	Change in CESD	**Change in Depression**
Young move	-0.061***	-0.043***
	(0.176)	(0.185)

*Notes: This table presents the ATTs along with their associated standard errors. These estimates are derived through PSM utilising one-to-one nearest-neighbour matching with a 1% caliper. Column (1) refers to changes in the CESD score, and Column (2) refers to changes in the probability of having depression. Data from the 2011 and 2013 waves of the CHARLS were used in estimation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

Table 2.7: Accounting for non-pecuniary losses

VARIABLES	**(1)** **Alone CESD**	**(2)** **Not Alone CESD**
Young move	-0.327	-0.631***
	(0.651)	(0.216)
Control variables	Yes	Yes
Observations	1,318	10,847
Number of id	694	5,820

*Notes: The table reports coefficients and standard errors (in parentheses). All models are estimated using a fixed-effects linear estimator. The dependent variable in all Columns is the CESD score. Data from the 2011 and 2013 waves of the CHARLS were used in estimation. Standard errors clustered at the household level are in parentheses. Time dummies and the interactions between provincial and time dummies are included in all models, but their coefficients are not reported for brevity. The definitions of all variables are provided in Table A.1. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

Table 2.8: Effect of the departure of members of the younger generation on consumption

VARIABLES	**(1)** **Consumption** **LogC**	**(2)** **Below Median ΔC** **CESD**	**(3)** **Above Median ΔC** **CESD**
Young move	0.357***	-0.562*	-0.575***
	(0.035)	(0.332)	(0.267)
Control variables	Yes	Yes	Yes
Observations	12,165	5,795	6,370
Number of id	6,514	3,047	3,467

*Notes: The table reports coefficients and standard errors (in parentheses). All models are estimated using a fixed-effects linear estimator. The dependent variable in Column (1) is LogC (Consumption), while in Columns (2) and (3), it is the CESD score for households with below and above median changes in consumption, respectively. Data from the 2011 and 2013 waves of the CHARLS were used in estimation. Standard errors clustered at the household level are in parentheses. Time dummies and the interactions between provincial and time dummies are included in all models, but their coefficients are not reported for brevity. The definitions of all variables are provided in Table A.1. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

Table 2.9: Taking into account the age of the leavers

VARIABLES	**(1)** **Full Sample** **CESD**	**(2)** **Below Median ΔC** **CESD**	**(3)** **Above Median ΔC** **CESD**
Young move	-0.076	-0.198	0.026
	(0.250)	(0.407)	(0.322)
Young move×Age 25+	-1.241***	-1.040	-1.379***
	(0.373)	(0.641)	(0.461)
Control variables	Yes	Yes	Yes
Observations	12,165	5,795	6,370
Number of id	6,514	3,047	3,467

*Notes: The table reports coefficients and standard errors (in parentheses). All models are estimated using a fixed-effects linear estimator. The dependent variable in all Columns is the CESD score. Data from the 2011 and 2013 waves of the CHARLS were used in estimation. Standard errors clustered at the household level are in parentheses. Time dummies and the interactions between provincial and time dummies are included in all models, but their coefficients are not reported for brevity. The definitions of all variables are provided in Table A.1. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

Table 2.10: Taking net transfers into account

VARIABLES	**(1)** $\Delta NT < 0$ **CESD**	**(2)** $\Delta NT \geq 0$ **CESD**
Young move	-0.509	-0.511**
	(0.419)	(0.235)
Control variables	Yes	Yes
Observations	2,818	9,347
Number of id	1,511	5,003

*Notes: The table reports coefficients and standard errors (in parentheses). All models are estimated using a fixed-effects linear estimator. The dependent variable in all Columns is the CESD score. Data from the 2011 and 2013 waves of the CHARLS were used in estimation. Standard errors clustered at the household level are in parentheses. Time dummies and the interactions between provincial and time dummies are included in all models, but their coefficients are not reported for brevity. The definitions of all variables are provided in Table A.1. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

Chapter Three

Financial Development and Mental Health

3.1 Introduction

Mental health issues have emerged as a leading cause of disease burden and a significant public health challenge worldwide, including in China. According to the World Health Organization (WHO), approximately one billion people worldwide were affected by mental disorders in 2019. In China, rapid social transformation over recent decades driven by urbanisation and modernisation has significantly altered residents' lifestyles and social structures, especially among the middle-aged and elderly. The shift from traditional agricultural settings to modern urban environments dramatically changes their social roles and daily routines, often resulting in social disconnection and isolation, negatively affecting their mental health (Chen et al., 2015; Guo et al., 2011). Cao and Zheng (2023) find that by 2022, 19.05% of older adults in China experienced mild depression, while 12.17% suffered from severe depression.

Socioeconomic factors have increasingly contributed to the mental health challenges faced by Chinese residents. For instance, rising living costs have introduced increased fi-

nancial strain (Chen et al., 2015). These financial pressures are further compounded by the fact that China's financial system lags behind advanced economies despite its substantial economic growth, particularly due to the dominance of state-owned banks. These banks have historically prioritised state-owned enterprises and large corporations, often neglecting small and medium-sized enterprises (SMEs) and individual households. Consequently, many Chinese households—especially in rural areas—face significant financing constraints due to underdeveloped financial infrastructure and limited access to diverse financial products and services (Demirgüç-Kunt and Klapper, 2013). Banks typically require high collateral to issue loans, which many households lack, further restricting their ability to secure credit (Cull and Xu, 2003). This is particularly problematic for middle-aged and elderly individuals with lower incomes, who struggle to obtain loans for critical needs, such as medical expenses (Liu et al., 2024; Yang et al., 2020; Banerjee, 2011).

Compared to developed countries such as the UK, China's public health insurance system offers relatively low reimbursement rates, leaving individuals to cover a significant portion of their medical expenses out of pocket, which creates additional financial burdens, particularly for the elderly (Wang et al., 2021b; Zeng et al., 2019). With China's rapidly ageing population and rising medical costs, many elderly individuals are forced to deplete their savings to pay for healthcare, exacerbating their financial pressures (De Nardi et al., 2010). Moreover, limited job opportunities and reduced income for the elderly—partly due to an inadequate pension system—make it difficult for them to access credit, forcing them to rely more strongly on personal savings and family support (Allen et al., 2012). These financial pressures not only diminish their quality of life but also contribute to mental health challenges, including anxiety and depression (Lund et al., 2010).

In this context, we use data on 20,725 individuals aged 45 and over taken from the CHARLS from 2011–2018. To assess the effects of financial development on people's mental health, we link CHARLS to a unique set of city-level financial development data, such

as the ratio of total bank and non-bank loans in the city's financial system to the city's gross regional product (GRP). Our results indicate that higher levels of local financial development are associated with significantly reduced depression rates among the population studied. Specifically, a one standard deviation increase in the ratio of total bank and non-bank loans to GRP, corresponds to a 1.9 percentage-point reduction in the probability of experiencing depressive symptoms. Our results are robust when using various specifications and different measures of financial development and estimation methods. Further investigation suggests that financial development benefits people's mental health by reducing the financing constraints that they face.

At the macro level, research has shown that financial development can significantly affect a country or region's overall health through various channels, such as reducing neonatal mortality and increasing life expectancy (Alam et al., 2016; Popoola, 2021; Cramer, 2021; Shi et al., 2022). However, few studies have explored the relationship between financial development and individual health outcomes, particularly mental health. Hu et al. (2024) examine the impact of interstate banking deregulation in the US on mental health by studying its influence on access to credit in a quasi-natural experiment. Their findings suggest that better credit conditions have a positive effect on mental health by reducing depression among low-income individuals, improving job prospects, and making it easier to obtain a mortgage. Conversely, the study also indicates that bank mergers and branch closures have a detrimental impact on mental health in the affected counties.

This study aims to broaden this work in several ways. First, we are the first to study the relationship between financial development and mental health directly. Second, we study the relationship between financial development and the occurrence of depression in the unique and relevant context of China, where depression is becoming increasingly prominent and the financial system is underdeveloped. Third, we use three macro databases to measure regional financial development, focusing on the dimensions of depth, accessibility, and digitalisation,

thus enabling us to provide a more comprehensive and objective approach than previous studies. Finally, we are the first to consider household-/individual-level financial constraints as a possible channel underpinning the association between financial development and mental health.

The remainder of the paper is organized as follows. Section 3.2 and Section 3.3 review the institutional background and economics background. Section 3.4 describes the gaps in the literature that our paper fills. Section 3.5 describes our data and presents some summary statistics. Section 3.6 describe our baseline specifications and methods. Section 3.7 presents the results. Section 3.8 provides further analyses. Section 3.9 concludes and provides policy implications.

3.2 Institutional Background

China's financial system and financing environment exhibit unique developmental characteristics and significant regional disparities. Despite rapid economic growth, the financial system is often considered underdeveloped compared to advanced economies (Wang et al., 2015). This underdevelopment is evident in the service capabilities of financial institutions, the depth and breadth of financial markets, and the pace of financial innovation (Min et al., 2018). In order to study the relationship between regional financial development and the mental health of residents, we first need to understand the background of financial development and financing constraints in China.

3.2.1 The Development of China's Traditional Financial System

After the founding of the People's Republic of China in 1949, the financial system was based on a highly centralised planned economy. The People's Bank of China (PBOC), as the only financial institution, assumed the dual role of central bank and commercial bank. The state strictly controls and allocates financial resources, providing financial support to state-owned enterprises mainly through budgetary allocations. During this period, personal financing was virtually non-existent, and services like personal and consumer loans were extremely limited. Individuals relied primarily on informal borrowing from friends and family to meet their financial needs (Liang and Jian-Zhou, 2006; Zhang and Chen, 2015; Guariglia and Poncet, 2008).

With the introduction of economic reforms and the "opening-up" policy, China's financial system gradually shifted toward magnetisation. The State Council authorised the creation of new financial institutions. Between 1978 and 1984, four state-owned commercial banks were established, each focusing on a specific service area: the Bank of China handled foreign exchange and trade, the China Construction Bank (CCB) focused on construction projects, the Agricultural Bank of China (ABC) served rural banking needs, and the Industrial and Commercial Bank of China (ICBC) addressed commercial and industrial activities in urban areas (Sara, 2019). During the 1990s, these four state-owned banks remained dominant, controlling 78% of the financial sector's total assets (Wu, 2019). However, personal financing was still in its infancy. Many individuals distrusted bank loans, and challenges like lengthy procedures, slow approvals, and high interest rates limited the reach of personal financing (He and Wei, 2023).

In 1993, China's financial system underwent significant reforms, leading to an increase in both the number and variety of financial institutions. Personal financing also began to expand. By 1998, the housing provident fund system was fully implemented, and personal

housing loans became more accessible, with the balance of such loans reaching RMB 126 billion by 1999 (China Financial Yearbook, 2000). However, the development of other personal loans lagged. Banks were cautious in their lending, imposing strict requirements on applicants' creditworthiness and repayment ability. This made it difficult for rural residents and low-income individuals to access loans (Yeung, 2009; Wang et al., 2017).

China's accession to the World Trade Organisation (WTO) in 2001 accelerated market-oriented reforms and the opening of its financial sector (Chen et al., 2011). The establishment of the China Banking Regulatory Commission (CBRC) in 2003 strengthened regulatory oversight of the banking sector. By 2010, the number of credit cards issued in China had exceeded 230 million (China Financial Yearbook, 2010). However, issues such as credit card defaults and overdue debts became increasingly prominent (Xia and Li, 2014).

3.2.2 The Rise of Chinese Digital Finance

The rapid development of digital finance and financial technology has significantly expanded access to financial services in China, particularly through third-party payment platforms and online lending systems. Peer-to-peer (P2P) lending platforms have played a critical role in broadening financing options for individuals, allowing them to obtain small loans through internet-based platforms. These financial innovations have alleviated financing difficulties for individuals and micro-enterprises, especially in areas underserved by traditional banks (Basha et al., 2021; Huang, 2018).

One of the most transformative innovations has been the rise of third-party payment platforms such as Alipay (launched in 2004 by Alibaba) and WeChat Pay (introduced in 2013 by Tencent). Initially developed for e-commerce, these platforms have evolved into comprehensive financial ecosystems, offering services such as microloans, wealth management,

insurance, and credit scoring. Alipay's "Ant Credit Pay" and WeChat Pay's "Weilidai" micro-lending products have provided millions of users with short-term, unsecured credit through entirely online application processes. This has greatly improved access to credit for individuals who might otherwise lack access to traditional banking services (Huang, 2020).

P2P lending has been another significant development, connecting borrowers and lenders directly via online platforms. "Paipaidai", launched in 2007, marked the start of a rapidly expanding industry, which by 2015 boasted over 3,500 platforms facilitating billions of yuan in loans (Hsu and Li, 2019). This filled a crucial gap for individuals and small businesses that were often excluded from traditional bank loans due to stringent lending criteria.

Digital finance has also greatly improved financial inclusion in China. By 2021, over 80% of Chinese adults had access to financial services through digital platforms (People's Bank of China). This digital revolution has been especially beneficial for underserved populations, such as rural residents and micro-enterprises, who previously faced significant barriers to accessing credit. Platforms like Alipay and WeChat have tailored products to meet these groups' needs, offering services such as micro-loans for agricultural production and mobile payment systems that reduce dependence on cash (Nemoto et al., 2019; Yu and McMorrow, 2021).

However, the rapid expansion of digital finance has also brought challenges, with fraudulent activities and risky practices emerging as significant concerns, particularly within the P2P lending sector. Despite showing initial promise in facilitating loans for individuals and small businesses, many P2P platforms collapsed due to insufficient regulation, leading to significant investor losses. By 2020, the Chinese government had introduced strict regulations that led to the closure of most P2P platforms, although regulated online lending channels continue to offer financing (He and Li, 2021). Additionally, the ease of access to digital

credit has raised concerns about over-indebtedness, particularly among young people and low-income individuals. With credit available at the click of a button, many borrowers have accumulated debts that they cannot repay, resulting in financial distress (Xie and Wu, 2023).

Overall, we illustrate the remarkable role of China's financial development in alleviating financing constraints from a historical perspective. The rapid development of China's financial system has significantly enhanced the diversity and accessibility of financial services, thus alleviating the financing constraints faced by individuals and enterprises (Ding et al., 2022).

However, China's financial system still strongly relies on banks, especially state-owned ones, which are more inclined to lend funds to large state-owned enterprises. At the same time, SMEs and individuals are often considered high-risk (Shen et al., 2009). Despite the population's high savings rate, it is often difficult for the general public—especially low-income groups—to obtain loans from traditional banks. In addition, the building of China's personal credit system started late, and banks have adopted a more conservative strategy in their lending decisions given that the lack of credit records makes it impossible to accurately assess borrowers' credit risk (Chi and Li, 2017; Naili and Lahrichi, 2022). The rise of Internet finance has brought new opportunities to ease personal financing constraints through providing convenient payment and credit services, whereby Internet companies such as Alipay and WeChat have made microcredit available to more individuals, especially in rural and remote areas not adequately covered by traditional financial services. Nonetheless, financing constraints still exist.

3.3 Economic Background

3.3.1 Financial Development and Mental Health

Only a few studies have linked financial development to mental health, with several studies focusing on the effects of credit conditions and financial inclusion on mental health. As important outcomes of financial development, inclusive finance and credit conditions reflect the financial system's efforts and achievements in promoting economic equality and improving economic efficiency. The formation and improvement of inclusive finance and credit conditions result from a combination of factors, including the maturity of financial markets, advances in fintech, improvements in regulatory policies, and changes in socioeconomic structure. First, the maturity of the financial market is the basis for improving inclusive financial and credit conditions. The development of financial markets has prompted an increased number of financial institutions, a broadened variety of financial products, intensified market competition, and expanded coverage of financial services. This includes not only the development of the traditional banking sector but also the rise of non-banking financial institutions such as credit unions and microfinance companies, which together provide a wider choice of financial services for different social strata, especially for low- and middle-income groups and SMEs (Beck et al., 2007; Demirgüç-Kunt and Klapper, 2012).

Hu et al. (2024) investigate the impact of laws affecting access to credit on mental health, presenting conflicting predictions. The authors use a quasi-natural experiment of interstate banking deregulation in the US between 1995 and 2005, as well as bank mergers and closures, to assess how bank regulatory reforms that improved credit conditions—e.g., by enhancing the efficiency of credit allocation and lowering lending rates—affected mental health. They use data from the National Longitudinal Survey of Youth 1979 (NLSY79), which includes detailed individual information on mental health assessed through the CESD-

7 scale. Their findings suggest that credit conditions have a significant impact on mental health. Specifically, they discover that among low-income individuals, these regulatory reforms reduced depression, boosted labour market outcomes, eased access to mortgage debt, and reduced the number of "unbanked" individuals. The authors suggest that improved access to credit can increase economic stability and reduce financial stress, leading to improved mental health outcomes. By contrast, they also find that mergers of large regional banks that led to branch closures and tighter credit constraints in affected counties harmed the mental health of lower-income individuals in treated counties.

Several other studies have explored the relationship between financial inclusion and mental health, with some showing a positive relationship while others find no relationship or even a negative relationship. These papers are discussed in the following.

Evidence from Countries Other Than China

Aguila et al. (2016) use bank account ownership to measure financial inclusion. Their target population is Hispanics over 50 and under 90 living in the United States from 2000 to 2012. They find that owning a basic financial instrument such as a bank account significantly and positively impacts mental health. Mental health in this study is measured using the CESD scale, which is a standard tool for assessing depressive symptoms. The authors highlight the importance of financial instruments in mitigating economic uncertainties and promoting a sense of security among older adults, which can alleviate symptoms of depression and anxiety. The authors explain their findings by suggesting that financial stability and reduced stress from having a bank account lead to improved mental health outcomes. Additionally, they note that these benefits are more pronounced for Hispanics in lower socioeconomic status neighbourhoods and those with below-median wealth, who face greater hurdles in accessing formal financial institutions.

Gigantesco et al. (2019) use Ghanaian data to evaluate the relationship between financial inclusion and the mental health of older adults, finding that having a bank account significantly improves mental health outcomes. Additionally, the study also measures financial inclusion through recent withdrawals, the use of ATMs, deposits, loans at local banks, and possession of a mobile money service account, whereby these measures show varied impacts on mental health. Mental health is assessed using standardised measures of depression and life satisfaction, specifically the Satisfaction with Life Scale (SWLS) and a validated depression screener. The authors explain their findings by suggesting that access to financial services provides a sense of security and control, which can alleviate stress and anxiety, thereby improving mental health. However, these two studies do not explain the causal relationship between mental health and financial inclusion.

Ajefu et al. (2020) explore the causal impact of financial inclusion on mental health among household heads in Nigeria. They use the 2SLS-IV model with the distance from home to the nearest financial institution as an instrumental variable for financial inclusion. Their findings suggest that financial inclusion improves mental health and reduces the likelihood of reporting depressive symptoms. The study uses data from the 2015/2016 Nigerian General Household Survey (GHS) and georeferenced data from the Insight2Impact (i2i) GIS interface. Mental health is measured using the CESD scale, where higher scores indicate worse mental health. Financial inclusion is defined through a multidimensional index comprising bank account ownership, credit access, and insurance access. The study finds that financial inclusion leads to a significant reduction in CESD scores and the probability of reporting depressive symptoms, highlighting the importance of accessible financial services in improving mental health. The authors address the potential endogeneity between financial inclusion and mental health by employing the 2SLS-IV approach, ensuring robust evidence of the causal relationship.

Evidence from China

Pham et al. (2018) investigate the relationship between financial development and the life satisfaction of entrepreneurs in China using the 2013 China Household Income Project (CHIP). They find no evidence of a link between financial development and entrepreneurial life satisfaction.

Similarly, Lu et al. (2023) uses cross-sectional data from the 2014 China Family Panel Study (CFPS) to study the mental health of Chinese employees. The difference compared to previous studies is that this study empirically identifies the impact of the Digital Inclusion Index (DIF) on employees' mental health using the 2014 CFPS data. The paper utilises multiple ordinal variables with values of 1 to 5 based on six questions from the CFPS data (feeling annoyed, nervous, agitated, hopeless, meaningless and difficult in the past month) to measure mental health. The authors find that DIF can help employees significantly improve their mental health. The study also reveals that the depth of DIF usage has a significant positive effect on mental health. In contrast, other sub-indicators, such as coverage breadth and degree of digital service provision, do not show a significant effect. Moreover, the positive impact of DIF is more pronounced among vulnerable groups, such as females and employees with lower education levels.

Tai et al. (2023) similarly focus on digital financial inclusion; however, they come to the opposite conclusion as Lu et al. (2023). They examine the relationship between DIF and life satisfaction in the over 60s, using data from the 2018 wave of the CHARLS. Their results consistently show that there is a significant negative relationship between DIF and life satisfaction in all models. This finding suggests that digital financial inclusion adversely affects the life satisfaction of the elderly. The authors explain this by indicating that the elderly face several challenges with digital finance, including a lack of familiarity with technology, difficulty in navigating digital platforms, and increased susceptibility to

financial fraud, which collectively leads to frustration and decreased life satisfaction.

These papers focus on the relationship between credit access/financial inclusion and mental health, both of which are direct results of financial development.

3.3.2 Financing Constraints and Mental Health

Financing constraints usually imply that individuals face barriers to accessing the financial resources necessary to meet their basic needs or to cope with emergency situations. These constraints can derive from a variety of reasons, such as a poor credit record, financial market situations, or even policy changes by banks and lending institutions. Stress theory suggests that when individuals encounter stressors, such as financing constraints, they need to access resources to deal with them. Suppose individuals are unable to obtain sufficient financial resources to solve problems or meet basic needs. In that case, this stress response can persist, which can lead to mental health problems such as anxiety and depression (Butterworth et al. (2009).

Some literature finds a positive association between people with financial constraints and depression (Lorant et al., 2007; Liu et al., 2021). A systematic study on financial stress and depression demonstrates that people with financial stresses, such as debt and financial hardship, are more at risk for depression (Guan et al., 2022). Literature also shows that the experience of financial constraints affects the psychological well-being of the elderly, increasing the risk of suicide and the risk of premature death (Tucker-Seeley et al., 2009; Fiksenbaum et al., 2017; Elbogen et al., 2020; Gillen et al., 2017). For example, Gillen et al. (2017) examines the impact of financial constraints on depression among adults aged 50 and older in the United States, using data from the Health and Retirement Study. Their results show that individual-level financial constraints significantly exacerbate depressive

symptoms, partly due to a diminished sense of financial control. This study highlights the profound impact of financial health on mental health and advocates for strengthening financial support systems to alleviate this psychological distress in older adults.

3.4 Contributions

Our contributions to the literature can be summarised as follows. First, we are the first to directly investigate the link between financial development and mental health. Advancing on previous literature that primarily explored the impact of credit access and financial inclusion on mental health, we measure the direct outcomes of financial development on mental well-being. This approach allows us to unveil novel insights into the broader impacts of financial system maturity on mental health.

Second, we are the first to study the link between financial development and the occurrence of depression in the context of China, a country characterised by poor financial development coupled with increasing problems of mental health. This unique context provides an important setting to explore how financial development can influence mental health outcomes. Our study aims to fill a significant gap in the literature by focusing on China, where the interplay between financial infrastructure and mental health has not been thoroughly investigated.

Third, we contribute to the existing literature, which generally uses credit access and the number of "unbanked" individuals to measure financial development. We use three macro databases to measure regional financial development along three different dimensions, namely depth, accessibility and digitalization. By accounting for multiple dimensions of financial development, our study provides a more nuanced understanding than previous studies (e.g., Pham et al. (2018) and Hu et al. (2024)) of how different aspects of financial

development influence mental health, particularly in the Chinese context. We also consider digital financial development, which is an increasingly important yet overlooked aspect.

Fourth, we are the first to analyze the role of financing constraints as a possible mechanism underpinning the association between financial development and mental health.

3.5 Data and Summary Statistics

3.5.1 Data

First, we use the CHARLS to collect detailed information on individuals' mental health status and family and personal attributes. CHARLS is a longitudinal survey of people aged 45 and older living in China and their spouses. Conducted by Peking University, the survey aims to understand the health and ageing issues of China's middle-aged and elderly population by tracking the health status, economic status, social relationships, and quality of life of the sample group over time. Based on a comparison of respondents' socioeconomic characteristics with national census data, Zhao et al. (2014) suggests that the sample is broadly representative of the Chinese population aged 45 and over. The survey started in 2011 and covered 28 provinces, 125 cities,150 county-level units, and 17,705 respondents. We use four waves of data collected in 2011, 2013, 2015, and 2018 for our analyses. These individuals were tracked over the subsequent three waves. The dropout rate between two successive waves is no more than 16%.

Next, we take our financial development variables from the China City Statistics Yearbook. We use data collected in the Yearbook to construct an index measuring city-level financial development. The Yearbook, published annually by China's National Bureau of Statistics (NBS), provides comprehensive, annually collated economic, demographic, envi-

ronmental, and social statistics at the prefecture-level city level in China. This paper focuses on three critical[1] financial data from the Yearbook: the year-end deposit and the year-end loan balances of financial institutions at the prefecture city level and each prefecture city's GRP. Our paper uses 2011, 2013, 2015, and 2018 data[2] to construct a city financial development index.

3.5.2 Sample Construction

We merge data from CHRALS and yearbooks by year and city. To this end, we prepare the CHRALS database, assembling a preliminary 4-wave panel dataset with 70,186 observations of respondents and their spouses, all aged 45 and older. In order to align with the Yearbook data, which only includes prefecture-level cities, we remove 2,137 observations from nine regions[3] not classified at this city level, and further exclude 3,243 observations without corresponding city-data. This refinement results in a dataset with 64,806 observations. We continue by excluding 5,431 observations where the main variable, the CESD score, is unreported, leaving us with 59,375 respondents. Additionally, we remove 4,047 observations with missing values in our control variables, bringing the total to 55,328 observations. Finally, we merge this refined CHRALS data with the Yearbook data, resulting in a final dataset that covers 116 cities and includes 55,328 observations. We also apply winsorization to all continuous variables at the upper and lower 1% quantiles to manage outliers. Figure 3.1 shows a flow chart of the sample construction process.

[1]The Yearbook presents two types of statistical data for each variable: "whole city" and "city district". To take into account any financial activities that may occur in any region of China and better match with CHARLS, we use 'whole city' data rather than 'city district' data for all city-level variables.

[2]Each year, the China City Statistical Yearbook contains data on prefecture-level cities across the country in the previous year. Therefore, the city-level variables for 2011, 2013, 2015, and 2018 are collected from the 2012, 2014, 2016, and 2019 editions of the China City Statistical Yearbook.

[3]The excluded cities are Xiongchu, Qiandongnan, Aksu, Enshi, Ganzi, Xinganmeng, Liangshan, Qiandongnan, and Xilingol.

3.5.3 Measures of Mental Health

To assess individuals' mental health, we use the 10-item Centre for Epidemiological Studies of Depression (CESD-10). The CESD-10 scale is a widely used mental health assessment tool specifically designed to measure an individual's self-reported frequency of depressive symptoms over the past week (Andresen et al., 1994). Several studies have confirmed that the CESD-10 scale has adequate reliability and validity for the Chinese population (Chen and Mui, 2014; Zhou et al., 2021). The CHARLS survey employs the Chinese version of the questionnaire, sourced from the official translation available on the Centre for Epidemiologic Studies website. The CESD is based on questions in which respondents rate the frequency of eight depressive symptoms (1 Feeling troubled, 2 Very annoyed, 3 Scared, 4 Agitated, 5 Everything is difficult, 6 Meaningless, 7 Frustrated, 8 Lonely) as well as two positive emotions (1 Feeling happy, 2 Hopeful) in the past week. Respondents' answers could be 1 = hardly ever, 2 = rarely, 3 = occasionally, and 4 = often. We score these responses following Radloff (1977) suggestion. Negative questions such as "Feeling troubled" are rated from 0 (hardly ever) to 3 (often). For positive questions such as 'Feeling happy', the ratings are reversed, ranging from 0 (often) to 3 (hardly ever).

The CESD scale consists of 10 items, each assessing the frequency of depressive symptoms on a scale from 0 (rarely) to 3 (most or all of the time), with a total score ranging from 0 to 30. Higher scores reflect more severe depressive symptoms. For our analysis, we follow Cheng and Chan (2005) to create the depression variable. This is a binary indicator that takes the value of 1 if the respondent's CESD score is 12 or higher, indicating the presence of depressive symptoms and 0 otherwise. In addition to our main variable, depression, we also explore more severe forms of mental health issues by generating a second dummy variable, severe depression, using a threshold of 20 or more on the CESD scale. This classification follows the guidelines of Radloff (1977) and Zhou et al. (2021), where a score of 20 or higher

signals severe depressive symptoms.

In addition, we consider life satisfaction as another indicator of mental health, a commonly assessed measure of mental health (Pavot and Diener, 2008). This indicator is based on the CHARLS questionnaire, "Are you satisfied with your life?". The answers range from very satisfied = 5 to dissatisfied = 1. The higher the score, the higher the life satisfaction. The original question on CHARLS for the above measure of mental health is provided in Appendix B.2.

3.5.4 Measures of Financial Development

We use three dimensions to measure city-level financial development: depth, accessibility, and digitalization.

Depth

As in Zhang et al. (2012), we construct two indicators to represent the overall depth of financial intermediation in the respondent's city. The first, *FinDev1*, is the ratio of total loans in the city's financial system (banks and non-bank institutions) to the city's GRP. This ratio indicates the extent to which credit is available and utilised within the city's economy. A higher ratio suggests a more developed financial sector capable of supporting economic activities through sufficient credit provision. *FinDev2* is the ratio of total deposits in the city's financial system to the city's GRP. This indicator reflects the savings behaviour of the city's residents and the capacity of the financial system to mobilise these savings for further financial and economic activities. Like *FinDev1*, a higher *FinDev2* ratio may indicate greater trust and participation in financial services by the general populace. According to Yang et al. (2022), these two indicators can be used to measure city-level financial development, as they

collectively measure both the credit and savings environments of cities.

Figure 3.2. shows the level of financial development of the 116 prefecture-level Chinese cities covered in the CHARLS in 2011 and 2018, as measured by the ratio of total loans in the city's financial system to the city's GRP. From 2011 to 2018, the financial development level of these cities in China has generally improved. The map shows significant differences in the level of financial development across Chinese cities. As expected, provincial capitals and coastal cities have the highest level of financial development. Conversely, the interior regions of China show a slower rate of increase in financial development, maintaining a disparity in financial growth across the country. The overall trend over these seven years shows that China's financial sector is deepening and expanding, especially in economically strategic areas such as provincial capitals and coastal cities.

Availability

We use the accessibility of regional financial development as an alternative proxy for financial development. This concept primarily refers to the prevalence and availability of financial services within a region, which is crucial for assessing the impact of regional financial development on residents' quality of life. Previous research, such as that by Demirguc-Kunt et al. (2008), indicates that high accessibility to financial services facilitates residents' ability to access essential services, such as loans, savings, and insurance, thereby enabling them to manage financial crises better.

We measure financial development from the perspective of service accessibility by following Tian et al. (2024) and utilising the China Stock Market and Accounting Research (CSMAR) dataset. The CSMAR dataset offers detailed information on the distribution of financial institutions across China, including the locations of bank branches and financial service points. Specifically, we construct two variables: n_bank_csmar and $n_bank_csmar_pc$.

The variable *n_bank_csmar* represents the total number of bank branches in each city. To construct this variable, we employ text analysis techniques to extract city names from the addresses of each bank branch listed in the CSMAR database. We then group the data by city and count the number of bank branches operating in each city. The status of each bank branch is determined by comparing its inception and closure dates, allowing us to identify whether a branch was operational in a given year. The total number of bank branches per city per year is then aggregated to form the *n_bank_csmar* variable.

The second variable, *n_bank_csmar_pc*, denotes the number of bank branches per 1,000 residents in a city. We calculate this by combining the *n_bank_csmar* data with population data from the city's statistical yearbook. This process allows us to account for population differences across cities, providing a per capita measure of financial service accessibility. The resulting panel dataset, covering the years 2011 to 2018, is then matched with data from the CHARLS for further analysis.

Digitalisation

The importance of measuring digital financial development lies in its potential to significantly enhance the ease and efficiency with which individuals access financial services, ultimately improving overall well-being and quality of life (Yang et al., 2023). In our study, we utilize the Peking University Digital Finance Development Index (PKU-DFIIC) to construct the variable *DFinDev*, which measures the level of digital financial development at the city level. The PKU-DFIIC, developed by the Digital Finance Research Centre of Peking University in collaboration with Ant Financial Services Group, reflects the penetration and development of digital financial services across various regions, including metrics such as mobile payments, the number of users on Internet financial platforms, and transaction volumes. This index is particularly useful for understanding how digitalization impacts financial inclusion, as it

captures the extent to which digital financial services are integrated into the daily lives of residents.

The PKU-DFIIC is a composite index that aggregates multiple dimensions of digital finance, including access, usage, and quality of digital financial services. *Access* measures the availability of digital services, such as the density of digital service points, including ATMs and bank branches. *Usage* reflects the extent of transactions conducted through digital channels, indicating the actual adoption of these technologies by individuals and businesses. *Quality* assesses the diversity and sophistication of available digital financial products, which contributes to an enhanced user experience and greater satisfaction. These three dimensions combine to form a composite score that represents the overall level of digital financial development in a region.

For our analysis, we use city-level indices from the PKU-DFIIC covering the years 2011, 2013, 2015, and 2018 to match the CHARLS data.[4] To ensure compatibility with other financial development indicators and to facilitate the interpretation of regression coefficients, we standardise the *DFinDev* variable by dividing the index values by 100. This allows for a consistent comparison across different measures of financial development.

The PKU-DFIIC's ability to capture the multifaceted nature of digital financial development makes it an invaluable tool for analysing the impact of digitalization on financial inclusion and economic efficiency. By reducing the cost of financial services and expanding access to underbanked populations, digital financial development plays a crucial role in improving financial services, particularly in developing regions (Yang et al., 2023). As such, the *DFinDev* variable derived from the PKU-DFIIC serves as a key indicator in our study, providing insights into how digital financial development influences the financial well-being

[4]In our previous matching of CHARLS and the yearbook, we excluded the data for nine non-prefecture-level cities that were missing in the yearbook. Although data for these cities are available in both the CSMAR database and PKU-DFIIC, we excluded them to maintain consistency in the dataset.

of local populations.

An introduction to the PKU-DFIIC database and a detailed explanation of the variables used in our study are provided in Appendix B.1.

3.5.5 Summary Statistics

Table 3.1 reports the means and medians for several key variables used in this study. The data shows that 26.8% of the respondents in the total sample have depressive symptoms. This is consistent with previous literature, which reports that the prevalence of depressive symptoms among the elderly in China is 26% and 27.1% (Li et al., 2019; Zhu et al., 2022). 6.9% of the respondents have severe depressive symptoms, which is consistent with Li et al. (2019). The summary statistics for the key independent variable, *FinDev1*, indicate a mean value of 0.949, with a standard deviation of 0.528 and a range from 0.254 to 4.029. These statistics suggest moderate variation in financial development across cities.

The mean age of respondents in our sample is 60.55 years, of which 48.3% are males and 86.2% of the sample are married. 60% of respondents in our sample live in rural areas. The education level of the respondents is poor: only 2% of the respondents in the entire sample have a college degree and above, and 10% of the respondents have high school degrees. The respondents' education level is generally low, as only 2% in the entire sample have a college degree and above, and 10% of the respondents have high-school degrees (Li et al., 2019). Focusing on regional financial development, the average ratios of total loans and total deposits to GRP are 94.9% and 140.8%, respectively, showing that the banking industry still dominates China's financial system. These ratios are consistent with the levels found in other studies focusing on China's financial development (Yang et al., 2022).

Table 3.2 presents the descriptive statistics of mental health variables by gender,

which is critical for several reasons. In China, traditional gender roles often impose different expectations on men and women, leading to varying levels of stress and divergent mental health outcomes. Women, in particular, might experience more significant psychological stress due to the dual demands of professional and family responsibilities, which can contribute to poorer mental health. Furthermore, societal norms might also lead to women more readily reporting mental health issues than men, potentially influencing the differences observed in mental health outcomes. Understanding these disparities is essential to identifying the specific challenges faced by each gender and developing more effective and equitable mental health support systems.

In Table 3.2, mental health variables are disaggregated by gender, with statistics for female respondents presented in Columns (1) and (2) and for male respondents in Columns (3) and (4). Column (5) highlights the mean differences between women and men, along with the statistical significance of these differences. The results indicate that women experience significantly worse mental health outcomes compared to men. Specifically, the mean CESD score for women is 9.295, notably higher than the mean score of 7.171 for men, with a highly statistically significant mean difference of 2.124. Additionally, 33.0% of women report a CESD score of 12 or higher, compared to 20.0% of men, resulting in a significant mean difference of 0.129. Furthermore, the probability of experiencing severe depression is 9.3% among women, compared to 4.3% among men, with a statistically significant mean difference of 0.050. Conversely, men report slightly higher life satisfaction scores than women, at 3.239 and 3.194, respectively. Although this difference is statistically significant, it is relatively small.

3.6 Methods

3.6.1 Baseline Specification

We investigate the relationship between regional Financial Development and residents' mental health by estimating the following model (Sturm and Gresenz, 2002; Gigantesco et al., 2019; Hu et al., 2024)

$$depression_{ijt} = \beta_0 + \beta_1 FinDev_{jt} + \gamma Z_{ijt} + v_i + v_t + \varepsilon_{ijt}, \tag{3.1}$$

where $depression_{ijt}$ is a dummy variable measuring whether individual i from city j at time t has depressive symptoms. $FinDev_{jt}$ is an index of financial development in city j where the respondent lives at time t. Z_{ijt} consists of a set of control variables, including demographic characteristics, socio-economic status, and respondents' physical health and lifestyle (Lauber et al., 2003; Takagi et al., 2013; Dour et al., 2014).

We are inspired by the literature related to the determinants of mental health in the selection of control variables. Firstly, we include gender, marital status, and age as respondents' demographic characteristics (Simon, 2002; Hopman et al., 2009; Takagi et al., 2013; Buckman et al., 2021). Many studies demonstrate that the prevalence of depressive symptoms increases with age (Woodall et al., 2010; Dour et al., 2014). This may be caused by the gradual onset of poor physical health, social isolation, and loss associated with ageing, which greatly increases the risk of mental health problems (Takagi et al., 2013). Therefore, we expect the sign of the coefficient associated with the continuous variable representing the respondent's age to be positive. Furthermore, some literature suggests that women are more likely than men to suffer from depression (Kuehner, 2017; Otten et al., 2021). In addition to biological factors such as hormones, women's social roles and social status may also

have an impact, making women more vulnerable to poverty than men, which may further lead to poorer mental health (Gigantesco et al., 2019). We construct a dummy variable equal to 1 if the respondent is male and 0 otherwise, and its coefficient is expected to be negative. Moreover, several studies find that marital status can influence mental health: married individuals show statistically lower rates of depressive symptoms. Compared with unmarried people, married people usually handle stress better because they have more coping resources and thus experience fewer depressive symptoms (Kessler and Essex, 1982). Cutrona (1996) also supports this finding, indicating that married people usually have lower rates of depression, which may be related to their stronger social support and emotional resources. Therefore, we expect to observe a negative correlation between marital status and depressive symptoms.

Second, a relationship has been established between lifestyle habits, such as smoking, drinking, sleep duration and social participation, and mental health (Daniel et al., 2004; Geoffroy et al., 2020; Du et al., 2022). Many scholars believe that smoking is negatively associated with depressive symptoms (Covey et al., 1990; Magee and Clarke, 2021). Alcohol intake is also correlated with mental health. Some studies find that moderate drinking is positively associated with both mental and physical health and that both excessive alcohol consumption and abstinence negatively affect health outcomes and predict worsening mental health (Bell and Britton, 2014; Castillo-Carniglia et al., 2019). Several studies find that sleep deprivation is positively associated with mental health outcomes such as depression (Chen et al., 2006; Scott et al., 2021). Other studies provide strong evidence of the positive impact of adequate sleep on mental health in older adults (Stone and Xiao, 2018). Therefore, we expect that individuals who do not smoke and get adequate sleep have a lower risk of depression. Individuals who drink alcohol may have either a higher or lower risk of experiencing depression. Also, social participation is critical for mental health. Previous studies find a strong positive correlation between social participation and mental health,

especially for the elderly (Chiao et al., 2011; Yue et al., 2022). Social participation provides emotional support and a sense of belonging to the elderly, helping to reduce loneliness and anxiety. In addition, it can promote an active lifestyle and improve the overall mental health of the elderly. Therefore, we expect to observe a significant negative association between social participation and the likelihood of experiencing depressive symptoms.

Third, we also control for respondents' physical health status and welfare factors, including chronic diseases, self-care ability, and participation in health insurance. Specifically, the prevalence of depression is significantly higher in individuals with chronic illnesses than in the healthy population. Chronic illnesses not only bring physical suffering but may also lead to psychological stress and anxiety (Katon et al., 2001). When individuals lose the ability to care for themselves, they may experience feelings of helplessness and loss, increasing the risk of depression (Bruce, 2001). Insurance can reduce the financial burden due to illness, enable individuals to receive timely medical help when facing health problems and reduce the risk of depression (McWilliams et al., 2004). Therefore, we expect that individuals with chronic illnesses and poor self-care (both Activities of Daily Living (ADLs) and Instrumental Activities of Daily Living (IADLs), will show a higher likelihood of suffering from depression.

Fourth, several studies generally find that people with low income, limited education, who do not work and who have fewer family members are at increased risk of having mental health problems (Sturm and Gresenz, 2002; Golberstein, 2015; Sperandei et al., 2023). Specifically, individuals with low incomes often face higher financial pressures to afford basic living and medical expenses, increasing the risk of anxiety and depression (Lorant et al., 2003). In this context, we include in our model a continuous variable that refers to the logarithm of the total household income of Chinese residents. Its coefficient is expected to be negative. We also include a series of dummy variables representing the highest level of education attained by the respondent. Individuals with low levels of education may lack the knowledge and resources to deal with mental problems and may also have unstable work

environments, further exacerbating mental health problems. Individuals with fewer family members may lack social support networks and a shortage of emotional and practical help when facing hardship, thereby increasing the risk of mental health problems. Therefore, we expect that people who live in large families may have a lower risk of experiencing mental health problems. Some literature confirms that those who do not work not only face economic hardship but may also suffer from psychological problems due to a lack of social roles and identity (Waddell, 2006). However, highly stressful jobs that lack security or involve poor working conditions, along with long hours and a lack of work-life balance, can contribute to increased anxiety and depression (Tennant, 2001). Therefore, people who do not work may have a higher or lower risk of depression.

Finally, in addition to the general determinants of mental health already described, we also include household registration as a control variable. China's household registration system (hukou) divides residents into non-agricultural and agricultural hukou.[5] People with agricultural hukou may face more socioeconomic constraints (Chan, 2013; Song, 2014). For example, rural residents have difficulty accessing local health insurance and medical resources, especially if they work in cities. They need to pay more for medical treatment or need to return to their original place of household registration to access their health insurance benefits. Therefore, we expect non-agricultural residents to have lower rates of depressive symptoms relative to agricultural residents.

The error term in Equation (3.1) contains the following components. v_i represents an individual-specific fixed effect, and v_t, a time-specific fixed effect. We account for the former

[5]China's hukou system is a state-implemented household registration system designed to manage citizens' residency and identity information. Originating in ancient times, the system's primary goals are to control population mobility, maintain social order, and document personal identity. The hukou system divides citizens into non-rural (urban) and rural categories, significantly impacting the distribution of social welfare, including education, healthcare, and housing. Individuals with urban hukou generally have better access to public services and social benefits than those with rural hukou. For instance, urban residents often enjoy superior education and healthcare, while rural residents may face limitations in these areas. Moreover, hukou classification affects eligibility for housing subsidies, pensions, and employment opportunities, leading to disparities in social welfare distribution between urban and rural populations (Chan, 2013; Song, 2014).

by estimating our model using a fixed-effects estimator and for the latter by including time dummies in our models. ε_{itj} is an idiosyncratic error term.

3.6.2 The Role of Financing Constraints

Financial development has been shown to alleviate financial constraints by improving access to credit and other financial resources (Karlan and Morduch, 2010). When financial constraints are reduced, individuals and households can obtain loans and credit more easily. This enables them to cope with economic shocks, invest in education and/or their businesses, and smooth consumption over time. This leads, in turn, to financial security, which can reduce the anxiety and stress associated with economic uncertainty, thereby improving mental health (Beck et al., 2007).

In summary, financial development can have a significant positive impact on people's mental health by reducing the financing constraints people face. In other words, financing constraints can be seen as the mechanism underpinning the association between financial development and mental health. If this is the case, then the mental health of individuals facing a higher degree of financing constraints should benefit more from financial development. To test whether this is the case, we estimate the following Equation

$$\begin{aligned} depression_{ijt} = \beta_0 + \beta_1 FinDev_{jt} + \beta_2 FinDev_{jt} \times FinancingConstraints_{ijt} \\ + \gamma X_{ijt} + v_i + v_t + \varepsilon_{ijt}, \end{aligned} \tag{3.2}$$

where $FinancingConstraints_{ijt}$ is a dummy variable equal to 1 if the individual is financially constrained in year t, and 0 otherwise. All other components of Equation (3.2) are the same as in Equation (3.1).

To measure financing constraints more accurately, we consider a set of individual char-

acteristics based on existing literature: educational level, age, consumption, and a variable indicating whether the respondent resides in a rural area. These characteristics have been shown to correlate with varying degrees of access to finance.

Individuals with lower educational attainment, particularly those with less than a middle school education, are often viewed by financial institutions as higher-risk borrowers (Bruhn and Love, 2014). This is because education is positively correlated with income potential, financial literacy, and access to formal employment opportunities, all of which enhance an individual's creditworthiness. Those with limited education may not only have fewer resources but also may lack the necessary financial knowledge to navigate the complexities of credit systems, further exacerbating their risk profile (Claessens and Perotti, 2007). Therefore, we expect people with low education levels to face more significant financing constraints.

Financial institutions typically view older individuals—especially those over the age of 65—as higher-risk borrowers, largely due to reduced income stability, increased health risks, and the shorter time horizon for loan repayment (Boisclair et al., 2017). Older borrowers might also have lower earning potential, which financial institutions can perceive as insufficient to meet repayment schedules, especially for larger loans. By contrast, younger individuals are perceived as having more years to build income and repay loans, thus facing fewer financing constraints. Accordingly, we include age as a variable and expect that those over 65 are more likely to face financing constraints.

Consumption patterns are often used as a proxy for income levels and overall financial health.[6] Individuals with low consumption levels are more likely to face financing constraints,

[6]According to Omar and Inaba (2020), consumption level is a more accurate indicator of financial status than income because it reflects the actual living standards and financial well-being of individuals. While income represents the inflow of money, consumption captures how resources are allocated to meet daily needs, thereby offering a clearer picture of economic stability and quality of life. Consumption accounts for savings, access to credit, and wealth, which income alone may not fully represent, especially in contexts where income is irregular or supplemented by non-monetary resources.

as low consumption might signal limited disposable income and reduced repayment capacity (Demirguc-Kunt et al., 2008). Financial institutions tend to view individuals with higher consumption as more financially stable and capable of managing debt, while low-consumption individuals may be perceived as higher-risk borrowers. Therefore, we expect individuals with low consumption levels to face more severe financing constraints.

Living in a rural area is a well-documented barrier to accessing formal financial services. According to Burgess and Pande (2005), residents in rural areas often face limited physical access to financial institutions due to underdeveloped infrastructure, fewer bank branches, and a lack of tailored financial products. Moreover, individuals in rural areas tend to have less formal employment, less stable incomes, and limited collateral, all of which contribute to higher perceived risk as perceived by financial institutions. This lack of access further compounds their ability to secure credit, meaning that rural residents are expected to experience higher levels of financing constraints than their urban counterparts.

In addition to these demographic and socioeconomic factors, physical health status plays a critical role in financial constraints in China, whereby residents are responsible for paying a significant portion of their medical costs. Individuals with chronic or serious illnesses often require frequent medical visits and long-term medication, resulting in high medical expenses. A considerable portion of these individuals' income is spent on medical expenses, reducing their disposable income and limiting their ability to save or invest, which restricts their financing capabilities (Liu and Mills, 2002). This reduced financial flexibility makes it difficult for them to cope with unexpected financial needs, such as emergency medical bills or other essential living expenses. Consequently, individuals in poor physical health are more vulnerable to financial constraints (Yip and Hsiao, 2009).

To capture this, we measure financing constraints using four dummy variables: (1) a dummy indicating that the respondent perceives their health to be poor, (2) a dummy

indicating that the respondent suffers from at least one middle-grade or severe chronic disease (e.g., diabetes, cardiovascular disease, cancer), (3) a dummy indicating limitations in IADLs, and (4) a dummy indicating limitations in ADLs. Including ADLs is crucial as they capture basic functional limitations such as difficulties with bathing, dressing, or eating, which often lead to higher medical expenses and reduced earning potential. Definitions for all financing constraint dummy variables are provided in Table B.1.

We are mainly interested in the interaction term between the level of financial development and the vulnerability to financing constraints. If the coefficients associated with financial development and the interaction term are both negative, this indicates that financial development has a stronger beneficial impact on the mental health of residents who are more susceptible to financing constraints.

3.6.3 Estimation Methodology

To estimate the impact of financial development on mental health while accounting for unobserved individual-specific heterogeneity, we primarily employ fixed-effects (FE) estimators.

When the dependent variable is binary, especially for depressive symptoms and severe depressive symptoms, in addition to the FE estimator, we also apply the correlated random effects (CRE) Probit estimator in the robustness test. CRE estimator was initially proposed by Mundlak (1978) and later adapted by Wooldridge (2019). This estimator parameterises the individual-specific error component as a function of the time averages of the time-varying explanatory variables, effectively controlling for any correlation between the unobserved heterogeneity and the explanatory variables.

3.7 Empirical Result

3.7.1 Main Results

We first present the fixed effects estimates of Equation (3.1) in Table 3.3 for the full sample (Column 1), for males (Column 2) and for females (Column 3). Column (1) reports the coefficients of the main independent variable and all control variables in the linear fixed effects model, which is used to estimate the determinants of the probability of having depressive symptoms in our full sample. We observe a significant negative correlation between financial development and having a risk of depressive symptoms in the full sample (Column 1). Specifically, a one standard deviation increase in the ratio of total bank and non-bank loans to GRP in the city where the respondent is based, corresponds to a 1.9 percentage-point[7] reduction in the probability of experiencing depressive symptoms. This corresponds to a decrease of 7.09% (1.9% / 26.8%) relative to the sample mean of 26.8% for *depression* reported in Table 3.1, so this effect is economically significant.

Our findings show that there is a significant negative correlation between financial development and the probability of residents showing depressive symptoms in Chinese cities. Our findings are consistent with existing literature. First, financial development provides residents with more economic opportunities and financial resources (Beck et al., 2007). When individuals are better able to cope with economic challenges and achieve their personal goals, they are less likely to suffer from depression (Lusardi and Mitchell, 2014). Second, a wider range of financial services and products can help residents better manage their wealth and diversify their risks, improving their ability to cope with economic fluctuations (Claessens and Laeven, 2003). This increased sense of economic security can increase residents' confidence in the future and reduce anxiety and fear of uncertainty, thereby reducing the risk of depression.

[7]This effect size is calculated as the product of the coefficient for FinDev1 (-0.036) and the standard deviation (0.528, see Table 3.1).

Finally, it has been shown that financial development can help reduce poverty and inequality, economic factors that are strongly associated with depressive symptoms (Beck et al., 2007). By providing a wider range of financial services and products, financial development can help individuals and households to better manage economic risks and enhance their economic stability and mental wellbeing (Honohan, 2004).

Column (2) and Column (3) of Table 3.3 present estimates of Equation (3.1) for males and females, respectively. The rationale for analysing gender differences is based on the understanding that men and women interact with financial systems in different ways, leading to potentially distinct impacts on their mental health.

Research shows that men and women have different financial behaviours, such as risk tolerance, saving habits, and financial decision-making (Denton et al., 2004). Women, for instance, tend to be more risk-averse and might engage less with financial products that are perceived as risky. This difference means that financial development—which includes expanded access to financial services like credit, savings, and investments—might affect women differently than men. Specifically, because women might start from a position of lower engagement with financial markets, the increased access and security brought about by financial development could have a more substantial impact on their mental health.

Furthermore, women are generally more prone to depression than men, partly due to the unique social and economic pressures they face (Piccinelli and Wilkinson, 2000). In contexts where women may have fewer economic opportunities and greater domestic responsibilities, financial development could play a significant role in improving their mental health by providing greater financial autonomy and reducing stress related to economic insecurity. For example, access to credit and financial services can help women manage household expenses more effectively, thereby alleviating some of the stress that contributes to mental health issues.

The results in Table 3.3 show that financial development has a more pronounced positive impact on women's mental health compared to men's. The significant coefficient for women (Column 3) suggests that financial development may lead to greater improvements in women's mental health by providing them with new opportunities to enhance their financial independence and reduce economic stress (Swamy, 2014). For men (Column 2), while financial development also has a positive impact, it is not significant. This could be because men, who might already have greater access to financial resources and services, experience financial development as an enhancement rather than a transformative change.

Focusing on control variables, the estimates in Column (1) indicate a positive correlation between age and the probability of having depressive symptoms, suggesting that older individuals tend to experience higher levels of depression. This finding is consistent with previous studies that have shown an increase in depressive symptoms with age due to factors such as declining health, social isolation, and bereavement (Woodall et al., 2010). Women are more likely to suffer from depression compared to men. This gender disparity in depression prevalence has been well-documented in the literature, with possible explanations including hormonal differences, greater exposure to stressors, and differences in coping mechanisms (Kuehner, 2017). Secondly, married individuals usually show a lower likelihood of depression compared to those who have never married, are widowed, or divorced. Marriage is often associated with better mental health outcomes due to the emotional and social support provided by a partner, which can mitigate stress and promote psychological well-being (Gigantesco et al., 2019). On the other hand, the loss of a spouse through divorce or widowhood can lead to significant emotional distress and loneliness, increasing the risk of depression (Pan et al., 2022). Next, the higher the income, the lower the probability of depression for both men and women. Higher income levels are typically associated with better access to healthcare, higher living standards, and reduced financial stress, all of which contribute to lower rates of depression (Lorant et al., 2003). Financial stability provides

individuals with the resources needed to manage stress and maintain a healthier lifestyle, which can protect against the onset of depressive symptoms.

3.7.2 Robustness Tests

We conduct a series of robustness tests to check the validity of our results.

Correlated Random-Effects Probit Estimates

We first estimate our baseline model using various estimation methods. Table 3.4 presents the correlated random effects estimates of Equation (3.1) for the full sample (Column 1), males (Column 2), and females (Column 3). In the full sample analysis, Column (1) shows that a one standard deviation increase in financial development is associated with a 0.8 percentage-point decrease in the probability of experiencing depressive symptoms. For females, Column (3) reveals that a one standard deviation increase in financial development is linked to a 1.0 percentage-point reduction in the probability of depressive symptoms, whereas the impact on males is minimal, as indicated in Column (2).

These findings are consistent with the fixed effects estimates in Table 3.3, further reinforcing the robustness of our results. In particular, financial development has a positive effect on the mental health of local residents, with especially pronounced benefits for women. Additionally, the signs and significance of the control variables align with those reported in Table 3.3, further strengthening the credibility of our conclusions.

Using Different Measures of Mental Health

Second, the effect of regional financial development on the mental health of local residents may vary depending on how mental health is measured. Therefore, we use the continuous CESD score, life satisfaction, and the dummy variable severe depression as alternative proxies for mental.

The estimates, which are obtained using a linear fixed effects estimator, are presented in Table 3.5, where the independent variables are CESD scores in Column (1), severe depression in Column (2), and life satisfaction in Column (3). In Column (1), a one standard deviation increase in financial development is associated with a 0.162 unit decrease in the CESD score. According to Table 3.1, the average CESD score in our sample is 8.27. Therefore, assuming a one standard deviation increase in the ratio of total loans to GRP, the average CESD score decreases to 8.108. This result suggests that, in line with our baseline results, financial development significantly reduces depressive symptoms among residents. Further, Column (2) and Column (3) show estimates of the determinants of dummy severe depression and life satisfaction. We observe that a higher level of financial development is associated with a lower likelihood of showing severe depression among residents in Column (2). This result indicates that financial development can alleviate severe mental health issues by offering greater financial security and stability. This is consistent with studies indicating that financial stability and access to financial resources are crucial in mitigating severe depression (Patel et al., 2018).

In addition, we find no significant relationship between financial development and life satisfaction in Column (3). This lack of significance suggests that while financial development may improve specific aspects of mental health, such as reducing depressive symptoms, it does not necessarily lead to an increase in overall life satisfaction. One possible explanation is that life satisfaction is a broad and stable measure of well-being and is influenced by a complex

array of factors beyond just economic conditions. While financial development can directly reduce depressive symptoms by alleviating economic stress and increasing financial security, life satisfaction encompasses a more comprehensive evaluation of one's overall life, including long-term goals, cultural values, and personal expectations. Depressive symptoms are more immediately responsive to changes in financial conditions, as they are closely tied to feelings of financial strain and insecurity. In contrast, life satisfaction is less sensitive to short-term improvements in financial conditions. It is shaped by a wider range of influences, making it less likely to be significantly impacted by financial development alone. This explains why financial development has a pronounced effect that may reduce depressive symptoms but not necessarily enhance overall life satisfaction (Helliwell et al., 2018).

The estimates of the coefficients associated with the control variables are consistent with baseline results and the existing literature.

Using Different Measures of Financial Development

To ensure the robustness of our findings, we employ a range of city-level financial development indicators that align with the three key dimensions of financial development: depth, accessibility, and digitalization. These indicators are chosen for their ability to comprehensively capture the various aspects of financial development across different regions. For financial depth, in addition to the *FinDev1* used in the previous baseline regression, we also use the ratio of total deposits to the city's GRP, a well-established measure that reflects the Stability of the financial system to support economic activities. We utilize *n_bank_csmar* and *n_bank_csmar_pc*, derived from the CSMAR dataset, to assess financial accessibility. Additionally, digitalization is captured by the PKU-DFIIC, which tracks the penetration and impact of digital financial services. The validity of these indicators is supported by various studies (see e.g. Demirguc-Kunt et al. (2008),Yang et al. (2022) and, Yang et al. (2023)).

Table 3.6 shows the estimation results, with the dependent variable being the likelihood of depression. Each Column includes a different measure of financial development: Column (1) uses *n_bank_csmar*, Column (2) uses *n_bank_csmar_pc*, Column (3) uses *FinDev2*, and Column (4) uses *DFinDev*. The findings suggest that the coefficients associated with financial development are statistically significant, regardless of how we measure financial development. In all cases, higher levels of financial development are associated with a lower likelihood of depression in the population. These results suggest that our main findings are robust when using different city-level financial development indicators. By applying these diverse indicators, we ensure that our analysis provides a robust and comprehensive understanding of financial development's impact on the likelihood of depression, as evidenced by the consistent results across different measures.

In Appendix Tables B.2 to B.4, we also provide estimates of Equation (3.1) with different indicators of financial development for different mental health indicators, including CESD scores, severe depression, and life satisfaction. Additionally, in Tables B.5 and B.6, we present estimates for the impact of different financial development indicators on depression and severe depression using a correlated random effects Probit model. The results are consistent with our baseline model.

3.8 Taking Financing Constraints into Account

3.8.1 Financing Constraints Based on Personal Characteristics

Table 3.7 presents the results of the heterogeneity analysis, where each Column represents a different interaction between financial development and a specific indicator of financing constraints. The findings align with our expectations and are consistent with previous liter-

ature.

In Column (1), the interaction term between financial development and the dummy indicating whether the respondent is aged 65 or more ($FinDev \times Elder$) shows a coefficient of -0.020, which is significant at the 10% level. This indicates that older individuals, who are more likely to face financing constraints, benefit more than their younger counterparts from financial development in terms of mental health improvements. Specifically, for older adults, a one standard deviation increase in financial development is associated with a 0.1 percentage-point greater reduction in the probability of experiencing depressive symptoms compared to younger individuals. This finding is consistent with the literature suggesting that financial security can significantly reduce anxiety and stress, especially among the elderly, who often face higher medical expenses and lower income stability (Beck et al., 2007; Gillen et al., 2017). Rural residents appear to derive even more mental health improvements from financial development, as indicated in Column (2). This highlights the transformative impact of enhanced financial services in rural areas, where residents often face greater economic uncertainty due to limited access to financial institutions. As suggested by Burgess and Pande (2005), improved financial access plays a crucial role in stabilising rural economies and alleviating the stress associated with agricultural risks and fluctuating incomes.

When it comes to educational attainment (Column 3), the results show that individuals with lower levels of education, who often face greater financial constraints, experience more significant mental health benefits from financial development. Column (4) uncovers that individuals with a lower consumption ($FinDev \times Lowconsum$) benefit notably from financial development. The interaction term shows that a one standard deviation increase in financial development is associated with a 0.13 percentage-point greater reduction in the probability of depression for this group compared to individuals with higher consumption.

3.8.2 Financing Constraints Related to Physical Health Status

Table 3.8 presents the relationship between financial development and depression, with a focus on physical health conditions. Across all models, financial development consistently shows a negative and significant impact on reducing the probability of depression. In Column (1), the interaction between financial development and poor health ($FinDev \times Bad_health$) is negative and significant, indicating that individuals in poor health benefit more from financial development in terms of mental health improvements.

Column (3) shows that the interaction with IADL limitations ($FinDev \times IADL$) is significant and negative, further supporting the idea that financial development helps alleviate mental health burdens for those with more complex daily activity limitations. In Column (2), while the interaction between financial development and ADL limitations ($FinDev \times ADL$) is not statistically significant, the negative coefficient still aligns with our conclusion that financial development generally reduces the likelihood of depression, even for individuals with basic functional impairments.

Finally, Column (4) reveals a significant negative interaction between financial development and chronic conditions ($FinDev \times Severchronicdum$), suggesting that financial development is particularly beneficial for those with severe health issues. Overall, the results reinforce our conclusion that financial development has a positive impact on mental health, particularly for those facing physical health challenges. Even where significance is not reached, the negative coefficients underscore the overall trend.

In summary, the results from Table 3.7 and 3.8 indicate that financial development has a more pronounced positive impact on the mental health of individuals who are more financially constrained. The significant interaction terms demonstrate that those facing higher financing constraints, whether due to age, rural residency, lower education, lower con-

sumption, or poor physical health, experience greater mental health benefits from improved financial development. This underscores the importance of financial development in alleviating financial stress and promoting better mental health among vulnerable populations. These findings are in line with our expectations and corroborate existing literature on the relationship between financial development and mental health.

3.9 Conclusion and Policy Implications

Our study uses the CHARLS database between 2011 to 2018, along with a unique set of city-level financial development data, to provide robust evidence on how financial development influences individuals' mental health in Chinese cities. We find that higher levels of financial development are associated with improved mental health outcomes. This positive correlation holds across various specifications, financial development measures, and estimation methods. Notably, the beneficial effects are more pronounced for older individuals, those with poor physical health, rural residents, and individuals with lower educational attainment—groups likely to experience significant financing constraints. We conclude that financial development enhances mental health by reducing these constraints. Our findings suggest that making finance more accessible would have the added benefit of improving the mental health of the Chinese population.

Our paper has several strengths. First, it is the first to explore the relationship between regional financial development and mental health in the Chinese context. This is especially relevant given China's uneven financial development, which leaves many people facing substantial financial constraints and limited access to credit and services. At the same time, mental health issues are rising, with many individuals experiencing stress and depression due to economic pressures. Understanding how financial development impacts mental

health is essential in addressing these challenges. Second, our study takes a comprehensive approach by assessing financial development through three dimensions: depth, accessibility, and digitalization. This provides a more detailed understanding of how different aspects of financial development affect mental health, especially in a rapidly evolving digital finance environment. Third, our study not only establishes a connection between financial development and mental health but also explores the role of financial constraints as a key contributing factor. We place special emphasis on groups that experience significant financial barriers, including the elderly, rural populations, and individuals with lower educational attainment. Our findings indicate that these groups gain the most from financial development, highlighting the critical role that alleviating financial constraints plays in enhancing mental health outcomes.

These findings have important policy implications. Policymakers should prioritise regional financial development as a means to address the mental health challenges facing China's population. Given the dominance of the banking sector in China's financial system and the government's influence on it, targeted reforms can expand access to financial services, particularly in underbanked rural areas (Burgess and Pande, 2005). Additionally, initiatives like the "Broadband China" strategy should be expanded to ensure that digital financial services reach disadvantaged groups. Such measures could substantially reduce financing constraints and improve mental health, as our results suggest (Lei et al., 2023). Technological advancements and regulatory improvements that increase the efficiency and reach of financial institutions can further ease financial stress, which often contributes to mental health issues (Hu et al., 2024). Given the rapid development of Internet infrastructure, promoting digital finance is critical for improving financial accessibility and convenience, particularly in remote areas. Targeted financial programs for vulnerable populations, such as subsidised loans, financial literacy initiatives, and enhanced social security measures, can also reduce financial stress and improve mental health (Lusardi and Mitchell, 2014).

One limitation of our study is the potential underreporting of mental health issues due to cultural stigma in China (Yin et al., 2020), which may lead to an underestimation of the association between mental health and other factors. Additionally, unobserved variables not accounted for in our analysis could influence both financial development and mental health, confounding the results. While we find strong associations, we cannot conclusively establish causality. Future research should explore this issue using instrumental variables or natural experiments to establish a more definitive causal relationship.

Figures and Tables for Chapter 3

Figure 3.1: Flowchart of sample construction process

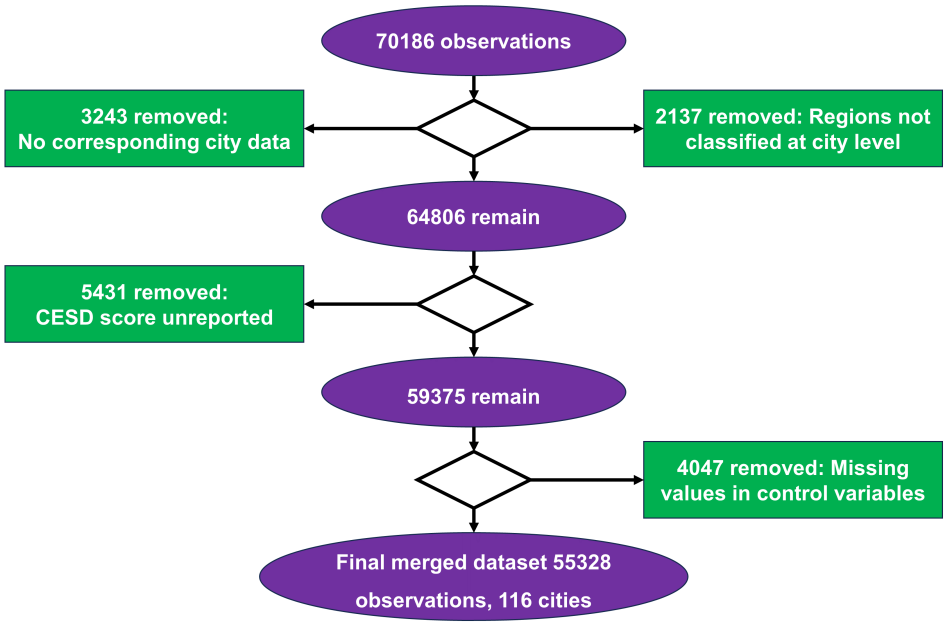


Figure 3.2: City-Level Financial Development in China (2011)

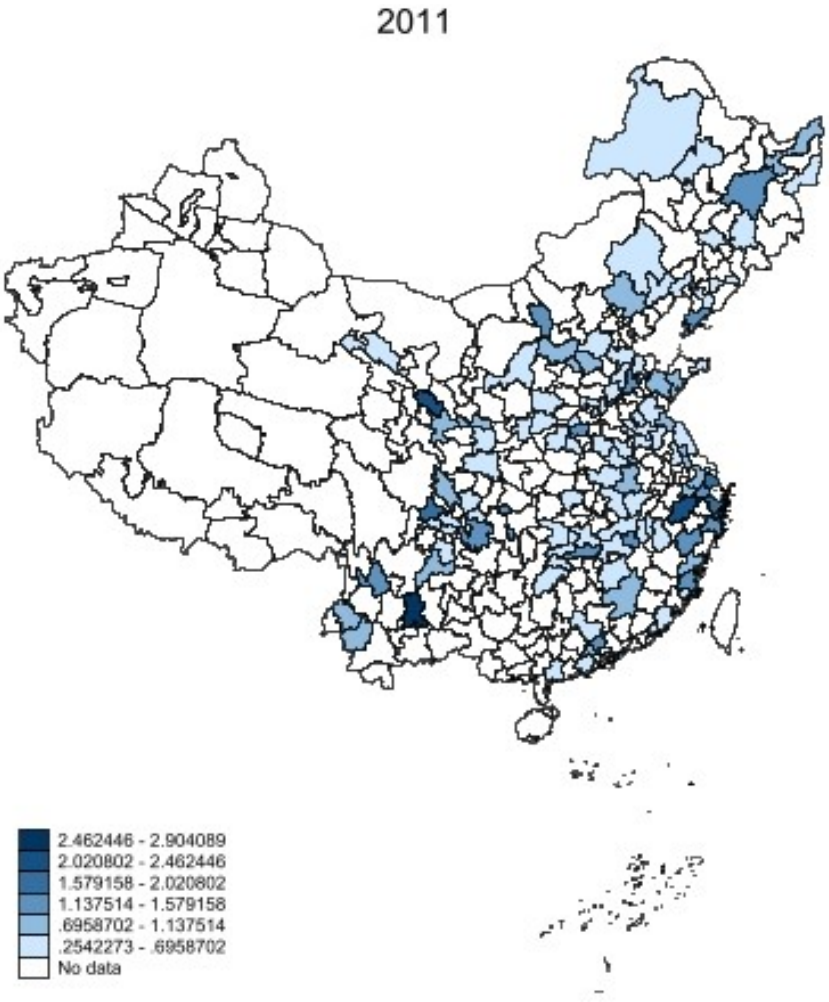
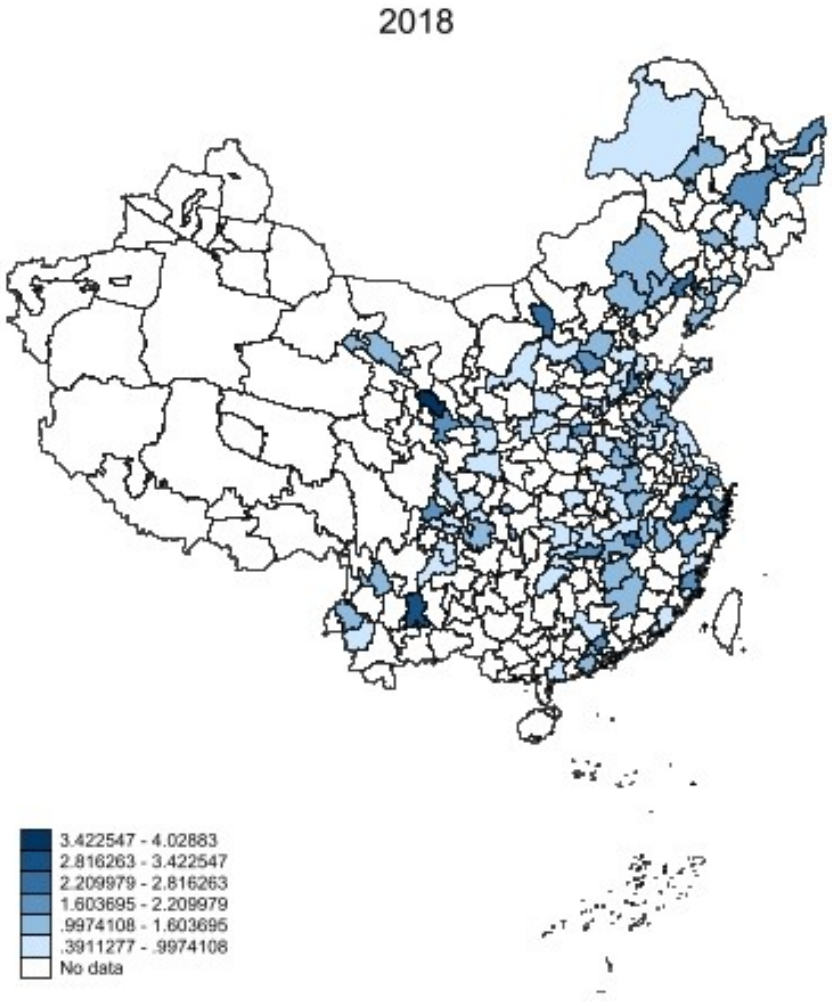


Figure 3.3: City-level financial development in China (2018)



Note: This figure presents the city-level financial development in China in 2011 and 2018. A city's financial development level is measured by the ratio of total loans (from both bank and non-bank institutions) in the city's financial system to the city's GRP.
Source: China City Statistical Yearbook.

Table 3.1: Descriptive statistics

VARIABLES	(1) N	(2) Mean	(3) Sd	(4) Min	(5) Max
Mental Health					
CESD	55,328	8.279	6.377	0	30
Depression	55,328	0.268	0.442	0	1
Life satisfaction	56,086	3.216	0.776	1	5
Severe depression	55,328	0.069	0.254	0	1
Control Variables					
Age	55,328	60.55	10.12	45	102
Male	55,328	0.483	0.5	0	1
Working	55,328	0.343	0.475	0	1
Hukoudum	55,328	0.226	0.418	0	1
Rural	55,328	0.593	0.491	0	1
Hyhhsize2	55,328	0.324	0.468	0	1
Insurance	55,328	0.947	0.224	0	1
Illiterate	55,328	0.256	0.437	0	1
Elementary	55,328	0.404	0.491	0	1
Middle school	55,328	0.211	0.408	0	1
High school	55,328	0.105	0.306	0	1
College	55,328	0.0243	0.154	0	1
Married	55,328	0.862	0.345	0	1
Divorced	55,328	0.0135	0.115	0	1
Widowed	55,328	0.117	0.321	0	1

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Table 3.1 – continued from previous page

VARIABLES	N	Mean	Sd	Min	Max
Never married	55,328	0.00786	0.0883	0	1
Chronics	55,328	1.636	1.609	0	13
Hour sleep	55,328	6.923	2.146	2	14
Social	55,328	0.544	0.498	0	1
Smoke	55,328	0.304	0.46	0	1
Drink	55,328	0.343	0.475	0	1
ADLs	55,328	0.393	1.043	0	6
IADLs	55,328	0.482	1.101	0	5
Lghhitot	55,328	9.032	2.746	0	15.62
Financial development					
FinDev1	55,328	0.949	0.528	0.254	4.029
FinDev2	55,328	1.408	0.562	0.498	5.313
DFinDev	55,328	1.488	0.680	0.195	3.029
n_bank_csmar	55,328	169.9	139.5	1	829
n_bank_csmar_pc	55,328	0.0708	0.0534	0.0057	0.392

Note: The descriptive statistics for all variables are derived from the sample used to estimate equation (3.1) *in the main results. The total number of observations is 55,328.*

Table 3.2: Descriptive statistics of mental health variables by gender

VARIABLES	**Female**		**Male**		**Mean-diff**
	(1) Obs	**(2) Mean**	**(3) Obs**	**(4) Mean**	**(5)**
CESD	28,356	9.295	26,972	7.171	2.124***
Depression	28,356	0.330	26,972	0.200	0.129***
Severe Depression	28,356	0.093	26,972	0.043	0.050***
Life Satisfaction	28,932	3.194	27,154	3.239	-0.045***

*Note: Columns (1) and (2) report the statistics of the mental health variables for female respondents, while Columns (3) and (4) report the statistics for male respondents. The "mean-diff" Column in Column (5) shows the differences in the means of the outcome variables between female and male respondents, along with Wald t-tests for the statistical significance of these differences. Definitions of all variables are in Table B.1. *** $p < 0.01$.*

Table 3.3: Baseline results: financial development and mental health; using the fixed effects estimator

VARIABLES	(1) ALL Depression	(2) Male Depression	(3) Female Depression
FinDev1	-0.036**	-0.011	-0.050**
	(-2.29)	(-0.53)	(-2.45)
Age	0.017*	0.000	0.033***
	(1.88)	(0.57)	(25.37)
Hukoudum	-0.252	0.005	0.042*
	(-1.44)	(0.57)	(1.65)
Married	-0.039***	-0.037**	-0.096
	(-3.01)	(-2.44)	(-1.09)
Nevermarried	-0.338	-0.035	0.122
	(-0.41)	(-0.88)	(0.99)
Widowed	0.194	-0.001	0.071
	(0.60)	(-0.06)	(1.48)
Illiterate	0.117	0.010	-0.037
	(0.26)	(0.48)	(-0.57)
Elementary	0.335	0.008	-0.019
	(0.78)	(0.40)	(-0.31)
Middleschool	0.128	-0.006	0.003
	(0.31)	(-0.28)	(0.05)
Highschool	-0.137	0.000	0.002
	(-0.37)	(0.00)	(0.04)
Hyhhsize2	-0.039**	-0.034*	-0.069***
	(-1.70)	(-1.17)	(-8.43)
Social	-0.046***	-0.025*	0.019
	(-4.69)	(-1.84)	(1.41)
Lghhitot	-0.031***	-0.021**	-0.023

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VARIABLES	ALL Depression	Male Depression	Female Depression
	(-3.06)	(-2.36)	(-0.61)
Smoke_now	-0.169	-0.002	-0.038**
	(-1.62)	(-0.37)	(-2.49)
Drink_now	0.032	0.008**	0.019*
	(0.42)	(2.28)	(1.72)
Insurance	-0.069	-0.050*	0.018
	(-0.60)	(-1.73)	(1.10)
Hoursleep	-0.037***	-0.009***	-0.021***
	(-24.54)	(-13.03)	(-10.17)
Chronics	0.017***	0.008***	0.027***
	(7.68)	(6.11)	(6.66)
Limitation	0.085***	0.026***	0.034***
	(37.63)	(29.71)	(12.70)
Working	0.027***	0.011***	0.033***
	(3.91)	(3.32)	(3.22)
Constant	17.530***	0.351***	2.059***
	(32.74)	(15.04)	(27.35)
Individual FE	YES	YES	YES
Time FE	YES	YES	YES
Observations	55,328	28,703	26,625
Number of id	20,725	10,699	10,026

*Notes: This table reports coefficients obtained using a fixed-effects linear estimator for the full sample (Column 1), males (Column 2), and females (Column 3), respectively. Time dummies are also included in all models, but their coefficients are also not reported for brevity. The dependent variable in all models is the probability of having depression. Data from the 2011 to 2018 waves of the CHARLS were used in estimation. T-statistics calculated using standard errors clustered at the individual level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

Table 3.4: Financial Development and mental health; using the CRE probit estimator

VARIABLES	(1) ALL Depression	(2) Male Depression	(3) Female Depression
FinDev1	-0.015***	-0.010*	-0.019***
	(-3.95)	(-1.93)	(-3.26)
Age	0.017*	0.000	0.033***
	(1.93)	(0.66)	(25.19)
Hukoudum	-0.225	0.006	0.042
	(-1.28)	(0.69)	(1.62)
Married	-0.056***	-0.038**	-0.102
	(-3.10)	(-2.51)	(-1.21)
Nevermarried	-0.135	-0.035	0.098
	(-0.16)	(-0.86)	(0.79)
Widowed	0.206	0.000	0.075
	(0.64)	(0.01)	(1.56)
Illiterate	0.115	0.010	-0.042
	(0.26)	(0.45)	(-0.65)
Elementary	0.321	0.008	-0.021
	(0.75)	(0.38)	(-0.34)
Middleschool	0.117	-0.006	0.000
	(0.28)	(-0.29)	(0.00)
Highschool	-0.132	-0.000	-0.000
	(-0.36)	(-0.00)	(-0.00)
Hyhhsize2	-0.047*	-0.032*	-0.069***
	(-1.84)	(-1.20)	(-8.35)
Social	-0.048***	-0.035*	0.012
	(-4.71)	(-1.90)	(1.38)
Lghhitot	-0.037***	-0.032**	-0.014
	(-3.05)	(-2.24)	(-0.64)

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VARIABLES	ALL Depression	Male Depression	Female Depression
Smoke_now	-0.161	-0.002	-0.038**
	(-1.53)	(-0.32)	(-2.49)
Drink_now	0.038	0.009**	0.019*
	(0.50)	(2.33)	(1.68)
Insurance	-0.080	-0.062*	0.015
	(-0.70)	(-1.91)	(0.90)
Hoursleep	-0.036***	-0.009***	-0.021***
	(-24.41)	(-12.90)	(-10.18)
Chronics	0.013***	0.008***	0.027***
	(7.52)	(6.09)	(6.58)
Limitation	0.086***	0.026***	0.034***
	(37.56)	(29.54)	(12.61)
Working	0.206***	0.011***	0.033***
	(3.75)	(3.17)	(3.15)
Constant	17.351***	0.344***	2.059***
	(32.32)	(14.70)	(27.26)
Observations	55,328	28,703	26,625
Number of id	20,725	10,699	10,026

*Notes: This table reports marginal effects obtained using a CRE Probit model for the full sample (Column 1), males (Column 2), and females (Column 3), respectively. The means of time-varying variables are included in all models, but their coefficients/marginal effects are not reported for brevity. Time dummies are also included in all models, but their marginal effects are also not reported for brevity. The dependent variable in all models is the probability of having depression. Data from the 2011 to 2018 waves of the CHARLS were used in estimation. T-statistics calculated using standard errors clustered at the individual level are in parentheses. The definitions of all variables are provided in Table B.1. * p<0.1, ** p<0.05, *** p<0.01.*

Table 3.5: Effects of financial development on different measures of mental health

VARIABLES	**(1)** **CESD**	**(2)** **Severe Depression**	**(3)** **Life Satisfaction**
FinDev1	-0.307**	-0.092*	0.014
	(-1.96)	(-1.32)	(1.54)
Control Variables	YES	YES	YES
Individual FE	YES	YES	YES
Time FE	YES	YES	YES
Observations	55,328	55,328	56,086
Number of id	20,725	20,725	21,595

Notes: The table reports the estimates of Equation (3.1) *using different measures of mental health. All models were estimated using a fixed-effects linear estimator. The dependent variable in Column (1) is the CESD score; in Column (2), it is the probability of having severe depression; and in Column (3), it is life satisfaction. Data from the 2011 to 2018 waves of the CHARLS were used in estimation. T-statistics calculated using standard errors clustered at the individual level are in parentheses. Time dummies are included in all models, but their coefficients are not reported for brevity. The definitions of all variables are provided in Table B.1. * p<0.1, ** p<0.05, *** p<0.01.*

Table 3.6: Effects of different measures of financial development on the probability of having depression

VARIABLES	**(1)** **Depression**	**(2)** **Depression**	**(3)** **Depression**	**(4)** **Depression**
n_bank_csmar	-0.001**			
	(-2.37)			
n_bank_csmar_pc		-0.014***		
		(-3.08)		
FinDev2			-0.038***	
			(-3.12)	
DFinDev				-0.095**
				(-1.70)
Control Variables	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	55,328	55,328	55,328	55,328
Number of id	20,725	20,725	20,725	20,725

Notes: The table reports the estimates of Equation (3.1) *using different measures of financial development. All models were estimated using a fixed-effects linear estimator. The dependent variable in all models is the probability of having depression. Data from the 2011 to 2018 waves of the CHARLS were used in estimation. T-statistics calculated using standard errors clustered at the individual level are in parentheses. Time dummies are included in all models, but their coefficients are not reported for brevity. The definitions of all variables are provided in Table B.1. * p<0.1, ** p<0.05, *** p<0.01.*

Table 3.7: The role of financing constraints; individual characteristic subgroup analysis

VARIABLES	**(1)** **Depression**	**(2)** **Depression**	**(3)** **Depression**	**(4)** **Depression**
FinDev	-0.025**	-0.034*	-0.026**	-0.066**
	(-1.74)	(-2.95)	(-1.82)	(-2.24)
FinDev × Elder	-0.020*			
	(-1.72)			
FinDev × Rural		-0.075**		
		(-2.11)		
FinDev × Lowedu			-0.040**	
			(-2.23)	
FinDev × Lowconsum				-0.024**
				(2.01)
Control Variables	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	55,328	55,328	55,328	55,328
Number of id	20,725	20,725	20,725	20,725

Note: The table reports the estimates of Equation (3.2) *using different measures of financing constraints. All models were estimated using a fixed-effects linear estimator. The dependent variable in all models is the probability of having depression. Data from the 2011 to 2018 waves of the CHARLS were used in estimation. T-statistics calculated using standard errors clustered at the individual level are in parentheses. Time dummies are included in all models, but their coefficients are not reported for brevity. The definitions of all variables are provided in Table B.1. * p<0.1, ** p<0.05, *** p<0.01.*

Table 3.8: The role of financing constraints; physical health subgroup analysis

VARIABLES	**(1)** **Depression**	**(2)** **Depression**	**(3)** **Depression**	**(4)** **Depression**
FinDev	-0.023*	-0.026*	-0.030**	-0.024*
	(-1.65)	(-1.85)	(-2.07)	(-1.71)
FinDev × Bad_health	-0.021*			
	(-1.83)			
FinDev × ADL		-0.017		
		(-1.50)		
FinDev × IADL			-0.022*	
			(-1.76)	
FinDev × Severchronicdum				-0.022**
				(-2.15)
Control Variables	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	55,328	55,328	55,328	55,328
Number of id	20,725	20,725	20,725	20,725

Note: The table reports the estimates of Equation (3.2) *using different measures of financing constraints. All models were estimated using a fixed-effects linear estimator. The dependent variable in all models is the probability of having depression. Data from the 2011 to 2018 waves of the CHARLS were used in estimation. T-statistics calculated using standard errors clustered at the individual level are in parentheses. Time dummies are included in all models, but their coefficients are not reported for brevity. The definitions of all variables are provided in Table B.1. * p<0.1, ** p<0.05, *** p<0.01.*

Chapter Four

The Link Between Internet Use and Overweight/Obesity

4.1 Introduction

China overtook the United States as the nation with the highest obese population in 2014, with approximately 90 million Chinese adults classified as obese. In contrast, approximately 78 million adults in the United States were classified as obese in the same year.(Ng et al., 2014). This is the first time that China has exceeded the United States as the country with the largest obese population. According to the "Report on the Status of Nutrition and Chronic Diseases of the Chinese Population (2022)", which is released biennially by the China National Committee on Nutrition and Food Safety and the Chinese Association on Nutrition, more than half of the Chinese population of the adults and one-fifth of the children's are subjected to the elevated risk for overweight or obesity. In addition to subjecting the population to serious health problems, the high prevalence of overweight and obesity has brought an increased burden on the Chinese medical and healthcare system.

Meanwhile, alongside economic and social development and rising income levels, the

Internet has rapidly gained popularity in China. According to the "47th Statistical Report on the Development of China's Internet" by the China Internet Network Information Centre (CNNIC), the number of Internet users in China had reached 989 million by December 2020, with an Internet penetration rate of 70.4%. In this group, urban Internet users account for 68.7% of the population.

Internet penetration has brought many changes to Chinese society. On one hand, the Internet has created new methods of information searching, communication, leisure and entertainment, making daily life more convenient. On the other hand, the Internet has impacted lifestyles and eating habits in China and may affect people's weight and lead to an increase in rates of overweight/obesity. Intuitively, increased Internet use could lead to prolonged periods of inactivity, which naturally diminishes physical activity levels, thereby contributing to weight gain (Suris et al., 2014; Tsitsika et al., 2016). Furthermore, excessive Internet use may disrupt regular meal patterns, promote snacking and consume more alcoholic beverages, which can degrade the quality of one's diet (Guo et al., 2021).

In developed countries, there is evidence showing the impact of scientific and technological information on overweight/obesity. Most research concerns the impact of watching television on overweight/obesity. The results confirm that excessive television time can limit energy expenditure and encourage overeating. Exposure to advertisements promoting unhealthy foods can also lead to overweight and obesity (Hancox and Poulton, 2006; Heilmann et al., 2017).

However, there is limited research on the effect of Internet use on overweight/obesity, and existing results are inconsistent. Studying the relationship between computer use and the risk of being overweight among Finnish adolescents, Kautiainen et al. (2005) find that girls who spend more time on the Internet are at greater risk of overweight/obesity than those who do not use the Internet. In contrast, Adachi-Mejia et al. (2007) use data from

the United States and find no significant relationship between the frequency of Internet use by children and their overweight status. Despite China's rapid Internet growth, there is a shortage of studies on the effect of Internet usage on overweight/obesity in the Chinese context. Chen and Liu (2022) explore an Internet speed upgrading project in China using a difference-in-differences analytical approach, focusing on urban residents. Their findings reveal that increased Internet access significantly reduces the incidence of overweight among urban residents.

Although the existing literature provides valuable insights into the relationship between Internet use and overweight/obesity, a thorough examination of this relationship, particularly within the Chinese context, remains lacking. This paper will make the following contributions. Studies to date have largely been limited to specific localities or demographic segments. This paper aims to extend these investigations by including a broader demographic and geographic scope. Unlike previous studies that may have concentrated on rural areas or adults alone, my research encompasses both urban and rural settings. It examines both adults and adolescents, providing a wider perspective on the issue. Moreover, while prior research has hinted at potential mechanisms by which Internet use could influence overweight/obesity, they have not been empirically tested in the Chinese context. This study will be among the first to empirically investigate nutrient intake as a mechanism affecting the relationship between Internet use and overweight/obesity among Chinese residents.

Based on the above background and motivation, I aim to explore the following questions: Does Internet use have an effect on overweight/obesity in the Chinese population? Are there any age and urban-rural differences in this effect? Finally, is the effect of Internet use on overweight/obesity in the Chinese population through the channels of nutritional intake, reduced physical activity, alcohol intake and sleep deprivation? To answer these questions, this paper will use the CHNS.

This paper facilitates a more comprehensive and multi-faceted understanding of the factors influencing overweight/obesity, which is an important prerequisite for addressing this growing health issue in China. Moreover, the socioeconomic distribution of overweight/obese people in China differs from that of developed countries. In European and American countries, people with higher socioeconomic status have lower rates of overweight/obesity (Sigmund et al., 2018). In China, the higher the income of men, the higher their rates of overweight/obesity (Zhang et al., 2017). Therefore, research concerning overweight/obesity in developed countries may not be applicable to China, necessitating research that focuses specifically on overweight/obesity in the Chinese population.

The remainder of this paper is organised as follows. Section 4.2 reviews the relevant literature on the determinants of overweight/obesity in general and the impact of Internet use on overweight/obesity and its mechanisms, in particular. Section 4.3 presents the gap in the literature that this paper fills, and Section 4.4 proposes the hypotheses to be tested. Section 4.5 outlines my data and variables, Section 4.6 and Section 4.7 describes my empirical methods, and results. Finally, Section 4.8 conclude with several policy suggestions and future research directions.

4.2 Literature review

4.2.1 Overweight and Obesity

Overview of Overweight/Obesity

Overweight/obesity is a chronic metabolic disease, which is the state of excessive accumulation of body fat. Its occurrence is closely linked to genetics, poor dietary structure and reduced physical activity (Lee, 2007). In the past 30 years, one of the most significant social

changes worldwide has been a dramatic increase in the prevalence of obesity and overweight (Jaacks et al., 2019). In 2003, the World Health Organisation (WHO) declared that overweight/obesity had reached epidemic proportions and classified it as a chronic disease along with cardiovascular disease, diabetes, hypertension and cancer (Barroso et al., 2018).

The current criteria for determining overweight/obesity are based primarily on body mass index (BMI), waist circumference and body fat percentage (Flegal et al., 2009). The most widely used criterion is the BMI threshold value formulated by the WHO to classify the degree of overweight/obesity, with people with a BMI between 25.0 and 29.9 being overweight and people with a BMI greater than or equal to 30 being obese. BMI can be adjusted according to different regions and people to determine the criteria for overweight/obesity (Gallus et al., 2015). The working group on obesity in China summarised and analysed the BMI, waist circumference, blood pressure, blood glucose, blood lipid and related data of 240,000 people in 21 provinces, cities and regions in China and proposed a different BMI standard for Chinese people. Specifically, a BMI greater than 24 is the threshold for overweight Chinese adults, and a BMI over 28 is the threshold for obesity (Du et al., 2013).

The expanding obesity epidemic appears to have originated in high-income countries, but since the 1870s, adults and children in most middle-income and many low-income countries have also been impacted by the epidemic (Swinburn et al., 2011). In recent years, the obesity epidemic has reached global proportions (Friedrich, 2017). According to a 2016 report by the WHO, more than 1.9 billion adults worldwide who are over the age of 18 are above normal weight. Furthermore, the overweight/obesity rate is higher in developed countries than in developing countries, and among developed countries, it is highest in North America (Swinburn et al., 2011).

In the Chinese population, the prevalence of overweight/obesity has increased rapidly since the reform and opening up. Wang et al. (2021a) analyse 645,223 participants aged

18–69 years using data from the Chinese Chronic Disease and Risk Factor Surveillance. Their results show that the obesity rate among Chinese adults was 8.1% in 2018, compared to 3.1% in 2004, which represents a 2.5-fold increase over 15 years. Chinese children and adolescents also face a serious risk of overweight and obesity. According to Fan and Zhang (2020), the overweight rate among Chinese children and adolescents aged 6–17 years increased from 5.16% in 1992 to 16.23% in 2015.

Overweight/obesity can cause serious health damage. Several epidemiological studies have confirmed a strong association between overweight/obesity and a variety of chronic diseases (Barroso et al., 2018). The relative risk of some chronic diseases is significantly higher in obese people than in normal people. For example, the risk of diabetes and dyslipidaemia in obese people is more than three times greater than that of the rest of the population, and the risk of coronary heart disease, hypertension and osteoarthritis is more than two times greater (Grundy, 2004; Barroso et al., 2018).

Overweight/obesity not only affects one's health, but it also plays a significant role in social stratification, mate selection and even employment. Morris (2007) and Greve (2008), using data from the UK and Denmark, respectively, find that obesity significantly reduces the probability of employment; Cawley (2004) finds that obesity is associated with low wages in the US. In terms of marriage, Gortmaker et al. (1993) find that young overweight women and men are 20% and 11% less likely to be married after 7 years than their peers, respectively.

Thus, the rapid rise of overweight/obesity is becoming increasingly serious and poses significant risks to the population, becoming a major global public health problem.

Factors Affecting Overweight/Obesity

As overweight/obesity has become a serious global public health problem, identifying factors that may influence overweight/obesity can assist in reducing overweight/obesity rates. Numerous studies have found that the factors determining overweight/obesity include not only biological factors, such as individual genetics but also individual characteristics and behaviours, environmental factors and socioeconomic status (Zhang and Wang, 2004; Jaacks et al., 2019). Therefore, overweight/obesity in humans is caused by the interaction of multiple factors. Hereafter, I review the relevant factors causing obesity, excluding genetic factors.

First, overweight/obesity is closely related to age, gender, marital status and other personal characteristics. Many studies have shown that the prevalence of obesity increases with age and tends to decrease slightly after reaching a certain age – 50 for men and 65 for women (Chapman, 2008; Swinburn et al., 2011). The reason may be that as the human body ages, it has an increased chance of suffering diseases such as osteoarthrosis and experiencing a rapid decrease in physical activity, which greatly increases the risk of obesity (Chapman, 2008). Furthermore, some literature suggests that women are more likely to be overweight/obese than men (Flegal et al., 1998; Gallus et al., 2015). Foulds et al. (2011) find that obesity is lower among male indigenous residents of Colombia compared to females. This may be due to the physiological characteristics and reproductive needs of women, which lead to a greater tendency to deposit fat in the body. However, Chen et al. (2019) shows that in China, the rate of increase in overweight/obesity rates in men is greater than that in women. This may be due to the fact that men in China are more likely to drink alcohol, leading to an increased energy intake and a tendency towards obesity. Women are also more concerned with maintaining their weight and figure than men. Additionally, marital status can influence obesity. Sobal et al. (1992) find that the obesity rate among married individuals is higher than that of unmarried individuals. This may be because marriage often

leads to lifestyle changes, such as more regular meals and shared eating habits, which can increase calorie intake. Married individuals might also experience less pressure to maintain a certain body image compared to those who are single, potentially leading to less motivation for weight management. Furthermore, married life can sometimes involve reduced physical activity due to increased family responsibilities and less time for exercise.

Second, there is a relationship between poor lifestyle habits, such as smoking and alcohol consumption, and overweight/obesity. Most scholars believe that smoking is negatively associated with overweight/obesity (Dare et al., 2015; Courtemanche et al., 2018). For example, Fang et al. (2009) conclude that smoking reduces weight but that long-term smokers gain weight after quitting. Some dieters may even consider smoking as a means of weight loss; however, the harm of smoking is far greater than the harm of weight gain. Therefore, smoking to lose weight is highly inadvisable.

Alcohol intake is also correlated with overweight/obesity. Wannamethee et al. (2005) conduct a 5-year prospective study on the relationship between alcohol consumption and body weight, using a sample of 7,608 American men. Their results indicate that heavy drinkers have a significantly higher BMI than non-drinkers and light and moderate drinkers. At follow-up, the weight of heavy drinkers who reduced their alcohol intake was significantly lower than that of long-term heavy drinkers, which indicates that heavy drinking can cause weight gain. However, some scholars support the opposite view, and a study by Wakabayashi (2011) shows that alcohol consumption in moderation plays a positive role in reducing the incidence of obesity in men.

Furthermore, some studies indicate that health insurance is a factor affecting obesity. For example, Kelly and Markowitz (2009), using data from the Behavioural Risk Factor Surveillance System from 1993 to 2002, find a positive association between insurance coverage and BMI in the United States, with this phenomenon more prevalent among lower-income

populations. The authors also note that while insurance coverage increases the probability of being overweight, it does not have a significant effect on the likelihood of being obese. This may be because insurance coverage could lead to increased access to healthcare services, including preventive care, which might encourage weight management but is insufficient to address the more complex and severe factors contributing to obesity. Zhao et al. (2018) use CHNS data to investigate the effect of health insurance on obesity risk in rural China. They show that insurance coverage increases unhealthy lifestyles, which results in a greater likelihood of general obesity in women and abdominal obesity in men. This may be due to the presence of insurance-induced ex-ante moral hazard in rural China. Although health insurance increases the accessibility of medical services, it may also reduce insured persons' commitment to protecting themselves against the risk of illness. Individuals' lifestyles change significantly with participation in health insurance, showing greater engagement in unhealthy behaviours such as smoking, alcohol consumption, sedentary behaviour and high-calorie diets, leading to an increased probability of being overweight (Qin and Lu, 2014).

Third, the relationship between socioeconomic factors and health has long attracted the attention of researchers and is a common indicator in studies on the factors influencing health problems. Thus, there is a large body of literature demonstrating the association between socioeconomic factors, including education, income and occupation, and overweight/obesity(Morris, 2007; Zhang et al., 2017).

Several studies on developed countries generally support the negative association between socioeconomic factors and overweight/obesity, meaning that people with low income and limited education are at increased risk of obesity. In a review analysis of studies related to obesity in the United States between 1990 and 2006, Wang and Beydoun (2007) conclude that an increased risk of obesity occurs in low-income or low-socioeconomic status groups, such as those with low education levels in the US. They also identify a negative association between individual income, education and body weight.

Conversely, studies based on developing countries have found that the higher the socioeconomic status, the higher the likelihood of being overweight/obese (Monteiro et al., 2004; Seubsman et al., 2010). A systematic evaluation by Dinsa et al. (2012) indicates a positive association between income, education and obesity for both men and women in low-income countries. That is, wealthier and more highly educated individuals are more likely to be obese. The positive relationship between socioeconomic status and obesity becomes a negative one as the economic level of a country increases (Pampel et al., 2012). The reason for these inconsistent findings may be due to food scarcity in poor countries, where survival instincts cause people to consume more calories. In such countries, society as a whole thus uses overweight/obesity as a symbol of social prestige and attractiveness (Sobal and Stunkard, 1989; Seubsman et al., 2010). In China, income, education and occupation have also been shown to affect overweight/obesity (Zhang et al., 2017). Focusing on adults in Zhejiang Province, Xiao et al. (2013) conclude that education and obesity among women are negatively correlated, while income and obesity are positively correlated among men.

Finally, studies demonstrate that overweight and obesity are also influenced by the natural and built environments (Prince et al., 2012; Jia et al., 2021). Nicolaidis (2019) provides a comprehensive analysis of environment-dependent weight disorders, concluding that built environment factors are significant contributors to obesity. These factors include residential density, land-use mix, proximity to public transportation, accessibility of sports facilities, and the availability of food environments such as the distribution of restaurants. The built environment influences obesity by shaping residents' physical activity levels and dietary habits. For instance, neighbourhoods with higher residential density and better access to public transportation may encourage walking or cycling, while the availability of sports facilities can promote regular physical activity. Conversely, areas with a high concentration of fast-food outlets may lead to poor dietary choices, contributing to weight gain. Thus, the built environment plays a crucial role in either mitigating or exacerbating

obesity rates among residents (Handy et al., 2002; Belon et al., 2016).

4.2.2 Internet Usage

Overview of Internet Use

The Internet is a means of communication and a repository of global information resources (Wang et al., 2011). Internet use refers to connecting an electronic computer or cell phone to the Internet to conduct information inquiries and share information on the network. As an important platform for information exchange, the Internet has a significant societal impact and poses a great challenge to traditional lifestyles (Sun et al., 2020).

The Internet in China is developing rapidly. The number of Chinese Internet users and the frequency of Internet use have both quickly increased. According to the data of China Internet Network Information Centre (CNNIC), between June 2011 and March 2020, the number of Chinese Internet users rose to 903 million from 485 million, and the Internet penetration rate increased to 70.4% from 36.2%. Per capita, weekly Internet hours in the Chinese population grew from 26.1 hours in December 2014 to 27.9 hours in June 2019. Due to the COVID-19 pandemic, the number of weekly Internet hours per Chinese resident surged to 30.8 hours in March 2020.

As Internet technology evolves, a variety of Internet services have become available for personal use. For example, some people use the Internet as a research tool at work, and some use the Internet for games and other leisurely activities. People of different ages have different motivations and needs regarding Internet use, resulting in distinct choices of Internet content. For most adults, the Internet primarily satisfies communication, professional and leisure needs. For young people, the Internet primarily meets their communication and entertainment needs. They use Internet functions such as multiplayer games, messaging via

web pages or email, live chat and music (Atkinson et al., 2009; Van Deursen and Van Dijk, 2014).

Impact of Internet Use on Health

With the Internet's increasing popularity and the growing concern over health issues, studies on the relationship between Internet use and health have expanded. Many studies have analysed this relationship from different perspectives, reaching different conclusions.

On the one hand, some studies conclude that Internet users tend to have better physical and mental health (Bessière et al., 2010; Nie et al., 2017). Internet use increases individuals' access to health-related knowledge, which is beneficial to improving health literacy and promoting healthy behaviours (Aydın et al., 2015). Similarly, the Internet facilitates the dissemination of knowledge and allows more people to obtain health information (Aydın et al., 2015). Both healthy and unhealthy people can access health information through the Internet (Berland et al., 2001; Kontos et al., 2010). Further, Wang et al. (2021c) suggests that the Internet information environment is more conducive to the dissemination of health information than offline methods. Therefore, people are more likely to use the Internet to access health information and improve their health. Lyu and Sun (2021) examine the relationship between Internet use time and self-rated health in a sample of 7,193 older adults in China. They conclude that Internet use is strongly linked to an improved likelihood of older people staying healthy.

In addition, online health services and health communication platforms provide social support, which positively impacts individuals' health (Chou et al., 2009; Mano, 2014). Hong et al. (2017) study the relationship between health disparities and the digital divide in the Chinese population, suggesting that through the Internet, individuals can access the latest health information and greater social support. The Internet allows more timely and

informed medical decisions and adoption of health behaviours, resulting in better health outcomes. Jane et al. (2018) state that social media use can facilitate weight loss by providing social support and enhancing health interventions for individuals participating in weight management programs.

On the other hand, while the Internet has significantly benefited the population, increased Internet use also has negative effects on people's health (Wang et al., 2011; Sun et al., 2020). For example, excessive Internet use may lead to video game addiction and social media dependence, especially among young people, which increases health risks (Kuss and Griffiths, 2011). Furthermore, although Internet use can improve health and provide access to health information and services, some studies show that people may encounter misleading or inaccurate information online, which can have a very negative impact on their lives and health (Metzger, 2007; Chou et al., 2018).

Although the above literature provides great insight into the Internet's impact on health, deficiencies nonetheless remain in research on the relationship between Internet use and health. Firstly, most literature considers only whether Internet use is present or not, ignoring the impact of the length of Internet use on health. Secondly, most studies only consider older adults and adolescents, thus neglecting the young and middle-aged populations. Finally, most of the literature focuses on mental health, with far fewer studies on overweight/obesity. I will discuss some of these studies hereafter.

4.2.3 Internet Use and Overweight/Obesity

The Relationship Between Internet Use and Overweight/Obesity

Evidence From the United States Adachi-Mejia et al. (2007) use a longitudinal survey involving data from a 2002–2004 telephone survey of 2,343 public school students (9 to 12

years old) and their parents in New Hampshire and Vermont, USA. The authors ask whether the parent has Internet access at home and how often the child uses the Internet at home. The answers to these two questions are separated into the following categories: never, less than once a month, several times a month, several times a week, or more frequently. Whether a student is overweight is measured by parental reports of the child's height and weight. The child is considered overweight if their BMI is equal to or is greater than the 95th percentile for Age- and gender-standardised child BMI. The authors use logistic regression models to focus on the association between Internet use and weight but find no significant relationship between a child's Internet use frequency and being overweight.

Consistent with the results of Adachi-Mejia et al. (2007), Jackson et al. (2011) also believe that BMI status or being overweight is unrelated to Internet use. They distribute questionnaires to 482 children (with an average age of 12) in the Lower Peninsula of Southern Michigan, USA. After controlling for socio-demographic characteristics, Jackson et al. (2011) find that Internet use is not associated with BMI or being overweight. They conclude that although children may spend more time using the Internet, this is not the cause of the surge in overweight among young Americans. However, the sample of this paper is quite small, containing less than 500 children, which reduces the persuasiveness of the results.

Berkey et al. (2008) study whether excessive online entertainment increases weight and leads to being overweight or obese. Their data comes from more than 5,000 females (aged 14 to 21) across the United States who self-reported their height and weight as well as typical leisure time spent online in 2000 and 2001. The findings indicate that females who spend more time on the Internet show a substantially higher BMI. This effect disappears for females aged 18 and over, probably because these females are more likely to spend non-entertainment time on the computer studying or looking for work. However, this paper only focuses on females in a very specific age range and, as such, is not representative.

Evidence From Other Developed Countries Kautiainen et al. (2005) draw similar conclusions to Berkey et al. (2008) when studying the relationship between watching TV, playing digital games, and using the computer and the risk of being overweight among Finnish teenagers. The authors collect data from 6,515 teenagers (aged 14, 16, and 18) in different regions of Finland through questionnaires in 2001. Kautiainen et al. (2005) then use multiple logistic regression to assess the association between time spent using three communication technologies (TV, video games, and computers) and overweight status among adolescents of different ages and genders. Their findings reveal a statistically significant link between increased computer usage and greater frequency of overweight among females but not among males. When taking age into account, they find that the relationship is only significant among 16-year-old females. The authors speculate that this could be due to a decrease in statistical power when the number of research participants decreases. As the male response rate in the sample is much lower than the female response rate, there may be more obesity-related possibilities in males who do not respond. Therefore, this may make the conclusion not completely convincing.

Bélanger et al. (2011) examine the relationship between different intensities of Internet use and somatic health in Swiss adolescents. Their data come from an anonymous 2002 questionnaire sent to 3,906 males and 3,305 females (aged 16 to 20 years old). Participants are divided into four groups according to the intensity of Internet use: heavy Internet users (over 2 hours/day), regular Internet users (less than 2 hours/day for several days per week), occasional Internet users (less than 1 hour/week), and non-Internet users (not used in the last month). Bélanger et al. (2011) suggest that males who use the Internet heavily are more likely to be overweight than regular Internet users. No association between Internet usage and overweight status is found for females.

Vandelanotte et al. (2009) also conclude that those who frequently use the Internet in their leisure time tend to be more overweight. Nevertheless, unlike Kautiainen et al. (2005)

and Bélanger et al. (2011), which focus on adolescents, Vandelanotte et al. (2009) target adults between 20 and 65 years old. The authors conduct surveys for 2,650 persons residing in Adelaide, Australia. The contents of their questionnaire include self-reporting height and weight as well as Internet use during recreational hours. Participants are divided into non-use, low use (less than 3 hours/week), or high use rates (3 or more hours/week). The results show that participants with high Internet use during leisure time have the highest rates of overweight/obesity and engage in fewer other activities than those who use the Internet less. Controlling for physical activity, age, gender, other sedentary behaviours, education, and employment, the authors show that participants who use the Internet during leisure time are 1.46 times more likely to be overweight than others. This paper clearly demonstrates the impact of Internet use on overweight/obesity. However, this study only examines the impact of Internet use in leisure time and not the impact of Internet use at work.

Like Vandelanotte et al. (2009), Suris et al. (2014) also focus on the relationship between adolescent Internet use and obesity. However, Suris et al. (2014) pays attention to problematic Internet use (PIU), investigating the relationship between PIU and the physical status of Swiss adolescents. The authors conduct a cross-sectional survey of 3,067 eighth-grade students in 2012 (49.7% are male) and divide the students into two groups: regular Internet users and problematic Internet users. After controlling for sociodemographic and Internet-related variables, they find that students with PIU are more likely to be overweight. This paper validates the link between Internet usage and obesity via data analysis. However, the authors only examine PIU during leisure time, and it may be difficult to distinguish between school and recreational Internet use when adolescents self-report their Internet use.

Park and Lee (2017) also focus on PIU and suggest that overweight/obesity are positively correlated with PIU, using a larger nationwide sample than Suris et al. (2014). The authors examine the association between BMI, weight perception, weight control behaviours, and PIU in Korean adolescents. The data in this paper comes from the 2010 South Korean

Youth Risk Behaviour Network Survey of 37,041 males and 33,655 females between the ages of 7 and 12. According to BMI thresholds, participants are grouped into underweight, standard bodyweight, and overweight/obese. The authors also use the Korean Adolescent Internet Addiction Propensity Scale to assess problematic Internet use. This paper shows that overweight/obesity is positively associated with PIU in females and males, but being underweight is also associated with PIU. The authors argue that the government should pay particular attention to teenagers' incorrect weight-control habits and implement education initiatives to teach adolescents healthy weight control. This study includes data from a nationally representative sample of over 70,000 Korean students, which enhances the external validity of the findings.

Tsitsika et al. (2016) also focuses on the link between PIU and adverse health outcomes among teenagers. Instead of focusing on a single country, their data comes from a cross-sectional poll of 14 to 17-year-old teens in seven European countries: Germany, Greece, Iceland, the Netherlands, Poland, Romania, and Spain. The Internet addiction test (IAT), sociodemographic data, and lifestyle characteristics are all included in the anonymous self-completed questionnaire. The authors use logistic regression analysis to investigate the relationship between overweight/obesity and possible risk variables. They show that being overweight or obese is significantly and positively associated with social network use and total daily Internet use. The authors suggest that high Internet use takes substantial time, reduces physical activity and healthy eating behaviours, and may, therefore, be associated with overweight/obesity in adolescents. However, they do not perform an empirical analysis of these possible channels.

Barrense-Dias et al. (2016) find that Internet use hardly affects overweight/obesity. The authors follow 621 adolescents between the ages of 14 and 16 in Switzerland, dividing them into two groups depending on their weight: overweight and non-overweight. Participants report demographics, substance use, health status, and Internet usage. The authors

use logistic regressions to assess the determinants of becoming overweight. They find that the risk of becoming overweight is mainly influenced by an individual's original weight status rather than by excessive Internet usage. Consequently, their findings do not support the hypothesis that Internet usage has a detrimental influence on overweight/obesity. However, the authors use a small sample size of 621 adolescents, and their results are not representative.

Evidence From China Research on the link between Internet usage and overweight/obesity in China is limited. Li et al. (2014) investigate the influence of Internet addiction on obesity among middle school students in Xiangtan City, China. They construct a random sample of 1,201 middle school students from various schools. They then distribute questionnaires asking respondents about their age, gender, place of residence, grade level, family history of obesity, personal computer ownership at home, and average daily physical activity time. The Internet addiction status of the subjects is measured according to the Internet Addiction Diagnostic Scale of Middle School Students. The diagnostic scale has 13 questions, and participants mark a 1 for "YES" and 0 for "No", and a score greater than five is considered Internet addiction. They find, first, that the probability of obesity among Internet-addicted students is statistically significant and 1.840 times higher than that of non-Internet-addicted students. Second, even after controlling for gender and grade characteristics, students with Internet addictions continue to be a high-risk category for obesity, with their obesity likelihood being 1.54 times higher than that of other students. Finally, even after correcting other factors that affect the occurrence of obesity, they still find that students addicted to the Internet have a 1.342 times greater risk of being obese than other students. Thus, the authors' findings suggest that Internet addiction may be a significant cause of obesity in middle school students. Moreover, the authors also explain possible reasons for the findings, such as the sedentary behaviour of Internet addicts and lack of exercise. However, they do not provide tests for these explanations.

Kim et al. (2010) differs from Li et al. (2014) by only focusing on Internet addiction, using logistic regression to evaluate the relationship between the overall Internet use of Hong Kong college students and health-related behaviours and health outcomes. Using an August 2006 questionnaire of 2,433 first-year students at the Chinese University of Hong Kong, the authors ask questions about height, weight, and average daily online time. The results also show that compared with other students, heavy Internet users are more likely to be overweight. However, the collection of sample data in August happened during the college students' summer vacation. Therefore, it is uncertain whether these findings are consistent when the respondents are in school as the participants' self-reported online time is not representative, and the results are unconvincing.

Notably, Qiu et al. (2021) draws a different result from the other studies, finding a negative association between Internet use and obesity. Their assessment involves the association between TV viewing, computer use, and mobile phone use with BMI and obesity in a 2018 sample of 2,873 adults from Nanshan District, Shenzhen, China. The sample is divided into underweight, average weight, overweight and obese groups based on BMI thresholds published by the WHO. The author compares the time spent using each individual device (TV, computer, and mobile phone) as well as the combined total usage of devices among the four groups through analysis of variance. Compared with other participants, obese participants spent less time on computers and mobile phones. The author explains the reasons for the negative relationship between Internet use and obesity, noting that some young adults may use the Internet more while exercising. In addition, work pressure may lead to a lack of appetite and weight loss for participants who must work with computers for an extended time. Notably, the sample involves many young adults, accounting for 74.16% of the total sample size. Furthermore, the Nanshan District of Shenzhen is a common location for Chinese Internet companies, and most of the young people here use the Internet for work. Therefore, the sample selection of this paper is not representative.

Chen and Liu (2022) expand on previous studies by focusing on urban populations aged 18 to 65, analysing the impact of increased Internet access on body weight in China. They exploit a natural experiment—China's Internet speed upgrading project during 2000-2001—and use a difference-in-differences (DiD) approach to assess the effects of enhanced Internet access. The authors find that increased Internet access leads to a reduction in the incidence of being overweight, which they attribute to improved health behaviours and higher incomes, driven by better access to information and economic opportunities. However, a notable limitation of the paper is its focus on urban populations, overlooking the growing importance of Internet access in rural areas. As a result, the study highlights key trends in urban health but may miss the broader impacts of Internet use on health in rural settings, which is increasingly important for understanding the Internet's role in public health in China.

Evidence From Other Developing Countries Eliacik et al. (2016) study the relationship between Internet addiction and obesity in Turkish adolescents. Internet addiction is measured by responses to 35 questions from the Internet addiction test scale. The critical value of Internet addiction is 68.5, with a higher score indicating more significant problems related to Internet use. The results show that adolescents with Internet addiction are 3.295 times more likely to be obese than adolescents without Internet addiction. However, the sample size for this paper is very small, with only 71 obese and 64 non-obese adolescents, making the results unrepresentative.

Mengesha Kassie et al. (2020) study the relationship between Internet use and obesity in an African country. This cross-sectional study is based on 2016 data from 2,848 women (15 to 49 years old) in Ethiopia. The authors use a logistic regression model with a dependent variable of overweight/obesity among non-pregnant women, classified according to WHO BMI thresholds. The independent variable is Internet use, categorised as either not using

the Internet or using the Internet at least once a week. The results indicate that respondents who use the Internet at least once a week are twice as likely to be overweight or obese when compared with those who do not use the Internet. The authors suggest that a possible explanation is that people who use the Internet in Ethiopia are more likely to be from middle-class or affluent groups, which are the most likely to be obese in African countries.

Rana et al. (2021) also discovers gender disparities in the association between Internet usage and obesity, with comparable findings to Bélanger et al. (2011). Unlike earlier research that used the WHO BMI threshold for persons all over the globe, the authors use South Asian (SA) BMI criteria to classify overweight individuals (23 to 27). Moreover, the authors use an ordered logistic regression model to estimate the link between Internet usage and overweight/obesity among Nepalese people (aged 15 to 49 years old). Their findings reveal that those who have used the Internet in the previous 12 months are 1.55 times more likely to be overweight than those who have not used the Internet in the past year. Investigating the impact based on gender demonstrates that males who have used the Internet in the past 12 months are 1.79 times more likely to be overweight than males who have not used the Internet during that period. Females who have used the Internet are 1.36 times more likely to be overweight than females who have not used the Internet. Therefore, males who use the Internet on a regular basis are more likely to be overweight than females.

Summary of the Relationship Between Internet Use and Overweight/Obesity

Although some literature suggests that Internet use is not associated with overweight/obesity or that there is an inverse relationship between the two variables, most of the literature surveyed above suggests that Internet use has a positive effect on people's overweight/obesity status. Moreover, the effect has been found to differ depending on people's age, gender, and residence. Furthermore, the effects of Internet use also differ among people with different BMIs.

However, the literature surveyed above suffers from the following limitations. First, the mechanisms by which Internet use impacts overweight have not been sufficiently discussed. Second, most of the height and weight data in the literature are self-reported and may not be accurate. Finally, the studies on China are only region-specific, which means that the results cannot be generalised.

Mechanisms Underpinning the Association Between Internet Use and Overweight/Obesity

The existing suggests that Internet use can affect overweight/obesity through reduced physical activity, sleep deprivation, and influence on nutrition and alcohol intake (Berkey et al., 2008; Bayon et al., 2014; DiNardi et al., 2019). However, no empirical analysis has been conducted to test these channels. I will discuss these channels hereafter.

First, the reduction of physical activity due to excessive Internet use is one factor that increases the risk of overweight/obesity. Physical activity is an important way for humans to balance energy intake and expenditure. The likelihood of overweight/obesity can be reduced by undertaking moderate to heavy intensity physical activity (Duncan et al., 2012). However, most people are almost immobile when using the Internet. Internet use is a passive activity that does not require physical exertion and, therefore, is considered an insufficient substitute for physical activity (Suris et al., 2014; Tsitsika et al., 2016). Prolonged Internet use reduces the amount of time people spend being physically active, leading to less caloric expenditure than caloric intake and resulting in fat hoarding (Mineshita et al., 2021). Chastin et al. (2015) suggest that heavy Internet use may lead people away from more physical activity and lower their metabolic rate, thus leading to an increased risk of obesity. Furthermore, the increased income of residents and the rapid spread of the Internet in China predispose Chinese to a sedentary lifestyle. This leads to a decreasing level of physical activity and a

general lack of exercise among the Chinese population (Powell and Chriqui, 2011). Zhang et al. (2020) finds that Chinese adolescent obesity is not only related to a lack of physical activity but also to increased time in front of screens.

Second, another mechanism through which excessive Internet use may cause overweight and obesity is sleeping deprivation. With the development of the economy, an increasing number of households are equipped with Internet connections. As a result, many individuals, particularly students, are willing to sacrifice sleep time to access the Internet. This lack of sleep shortens the amount of time the body has to digest and recover completely. As a result, obesity has increased (Bayon et al., 2014; Chaput, 2016; Kokka et al., 2021). According to Reiter et al. (2012), less sleep and more Internet use are associated with higher BMI. In addition, Chapman et al. (2013) indicate that a decrease in daily sleep duration is associated with a rise in obesity levels in the United States. Similarly, Guo et al. (2021) finds sleep deprivation increases the risk of obesity among Chinese residents. Their results show that if the daily sleep time is less than 6 hours, the risk of obesity increases by 35-41%.

Third, unbalanced nutrient intake and excessive alcohol intake are also affected by Internet use, which simultaneously affects overweight/obesity. Excessive Internet use can cause poor dietary habits and inadequate nutritional intake. For example, skipping meals, especially breakfast, and eating large amounts of snacks may increase the risk of obesity and overweight. (Munro et al., 2011). With the rapid rise of the take-out industry in China, many Internet users there have increasing access to convenient and tasty but unhealthy food, affecting nutritional intake and leading to obesity (Wang et al., 2016). The easy availability of this food can reduce the dietary nutritional content and lead to overweight/obesity in the population.

Last, excessive Internet use is also associated with increased alcohol intake, and most literature demonstrates that alcohol intake affects overweight/obesity (Afshin et al., 2016;

Park and Lee, 2020). Svensson and Johnson (2020) study the association between Internet use and alcohol consumption using data obtained in 2016–2019 from 3,733 Swedish adolescents between the ages of 14 and 15 years old. Their results suggest a positive and significant association between Internet use and alcohol consumption, especially online social use. Fazzino et al. (2017) conducts a cohort study of 7,491 young Americans who consume alcohol, finding heavy alcohol consumption a potential risk factor for weight gain and conversion to overweight and obesity.

Although the above literature offers some potential mechanisms for the association between Internet use and overweight/obesity, further empirical analyses are needed to fully understand the details of these mechanisms.

4.3 Contributions

We contribute to the literature on the relationship between Internet usage and overweight/obesity by addressing several gaps and further expanding the relevant analysis. First, while existing research, such as Chen and Liu (2022), investigates the general relationship between Internet access and body weight, with a particular focus on urban areas, my study broadens the scope by examining both urban and rural populations in China. This broader geographical focus allows us to capture regional disparities in economic growth and lifestyle, providing a more comprehensive understanding of how Internet usage influences overweight and obesity across different demographic groups, including adults and children.

Furthermore, my study contributes to the literature by investigating the specific mechanisms through which Internet use influences overweight and obesity. This paper presents the empirical analysis of the impact of nutritional intake, including energy, fats, proteins, and carbohydrates, on body weight for the first time. Additionally, I empirically examine

other distinct pathways, such as alcohol consumption, sleep deprivation, and decreased physical activity. Through this comprehensive analysis, I provide a clearer explanation of how Internet use leads to changes in body weight, thereby offering a more detailed understanding necessary for addressing this phenomenon.

Lastly, I address the methodological limitations prevalent in much existing research, which often rely on self-reported BMI data. Self-reported measures of weight and height can introduce bias, leading to inaccurate assessments of overweight and obesity. My study improves upon this by utilising objective measurements of respondents' weight and height taken by nurses, thereby enhancing the reliability of my findings. Additionally, I supplement traditional BMI measurements with the waist-to-height ratio, providing a more nuanced measure of obesity that accounts for fat distribution, a critical factor in assessing health risks. Importantly, my analysis also employs BMI thresholds specifically calibrated for the Chinese population and provides age-specific BMI values for adolescents. These tailored measures ensure a more accurate assessment of obesity and overweight status in diverse demographic groups within China.

4.4 Hypotheses Development

The Internet has become the most often used instrument in people's everyday lives due to its quick expansion. Evidence from industrialised nations and China shows that Internet usage may increase the likelihood that a population is overweight or obese (Kautiainen et al., 2005; Li et al., 2014). In light of this literature, my first hypothesis reads:

H1: Internet usage among Chinese residents is positively associated with overweight/obesity.

Chinese men and women exhibit distinct patterns of Internet use, particularly when it comes to activities that impact health. Men, for instance, tend to spend more time on gaming and entertainment, activities closely tied to sedentary behaviour (Li and Kirkup, 2007). These extended periods of inactivity contribute to health issues such as weight gain and obesity, highlighting the potential for gender-specific health outcomes related to Internet use. Furthermore, studies like Su et al. (2019) emphasise that Asian men are significantly more prone to developing PIU and Internet addiction. These forms of excessive online engagement are associated with decreased physical activity and unhealthy lifestyle habits, both of which are linked to obesity. The gender disparity in how Internet use can lead to sedentary behaviour and weight gain suggests that this relationship may be stronger in men than in women. In light of these findings, I propose the following hypothesis:

H2: The association between Internet use and overweight/obesity among Chinese residents is stronger in males than in females.

Chinese society currently features a dualistic economic structure, and urban function regions are much more economically developed than rural areas, and the Internet penetration rate is much higher than in rural areas. In rural areas, increased use of the Internet may lead to greater lifestyle changes, as the habits brought by the Internet, such as higher duration of screens for extended periods and reduced physical activity, may have a greater impact than among urban dwellers. Rural areas are the traditional sites of more manual labour, and hence, the use of the Internet is more likely to contribute to reduced levels of physical activity. However, Chinese urbanites already spend much more time in China's increasingly automated workplaces. So, they are less likely to see adverse shifts in physical activity as an outcome of an increase in their Internet usage levels. Instead, I expect to see that Internet usage more strongly relates to overweight/obesity among rural residents. Thus, my last hypothesis is:

H3: The association between Internet use and overweight/obesity among Chinese residents is stronger in rural areas than in urban areas.

4.5 Data and Summary Statistics

4.5.1 Database

The data for this investigation was obtained from the CHNS. The database was created in collaboration with the Population Centre at the University of North Carolina in the United States and the Chinese Centre for Disease Control and Prevention's National Institute for Nutrition and Health. The first large-scale field survey in China was undertaken in 1989, comprising nine provinces (Liaoning, Heilongjiang, Jiangsu, Shandong, Henan, Hubei, Hunan, Guangxi, Guizhou) and three municipalities (Beijing, Shanghai, and Chongqing) which differ significantly in geography (see Figure 4.1), economic development, lifestyle, and food patterns. The CHNS study consists of 10 waves of data collection from 1989 to 2015.

The survey's content covers a wide range of topics, including health, nutrition, sociology, demography, economics, public policy, and many more. This data comprises not only dietary and health data but also fundamental information about respondents, such as age, marital status, education level, and so on. Furthermore, the dataset contains information on respondents' usage of information technology. It started asking if people had computers in their households in 2000. In 2004, they started to question respondents about Internet connectivity and usage. Relevant to my study, the database contains information on the daily time spent by Chinese residents on mobile phones and computers browsing, chatting, gaming, and watching digital TV. It also contains information about their diet and nutritional status, exercise time, sleep status, drinking status, height, weight, and waist circumference.

4.5.2 Samples

As information on Internet usage only started to be collected in 2004, my dataset only includes data from 2004 and beyond. Therefore, I initially obtain a five-period panel data containing 68,692 observations. Second, the questions on Internet usage are only asked to respondents aged 6 or above. We, therefore, drop 3,667 respondents younger than 6. Furthermore, weight is never a serious health problem for people over the age of 80. We, therefore, drop 7,768 respondents above the age of 80 from the sample. At this point, I am left with 57,263 observations. I also drop 3783 observations with missing height and weight data. Finally, I exclude 5150 observations with missing values for the variables included in the model. After adjustment, the sample data for this paper consists of 49,385 observations, 21,817 individuals, and five waves for the following estimates.

4.5.3 Variables

Indicators of Overweight/Obesity

This paper primarily employs two variables to assess obesity and overweight among Chinese citizens. First, I use the body mass index (BMI). Established as a standard measure for obesity by the WHO and the International Obesity Working Group in 1997, BMI is calculated as weight in kilograms divided by the square of height in meters (kg/m^2). For this study, I adhere to the Chinese-specific BMI thresholds. In China, an adult is classified as overweight with a BMI of 24 or higher and as obese with a BMI of 28 or higher. This is in contrast to the thresholds in the United States and the United Kingdom, where the BMI criteria for overweight and obesity are set at 25 and 30, respectively. The BMI thresholds for Chinese adolescents are adapted to account for age and gender variations and are detailed in Table C.2. In this paper, I define my independent variables of overweight and obesity using

these BMI calculations, ensuring that my analysis is appropriately tailored to the specific physiological considerations of the Chinese population.

Second, I use the Waist-to-Height Ratio (WtHR) as a robust metric to assess obesity, following the methodology developed by Ashwell and Hsieh (2005). WtHR is calculated by dividing an individual's waist circumference by their height, both measured in centimetres (Waist cm / Height cm). A WtHR of 0.5 or higher indicates an increased risk of metabolic complications related to central obesity across different races, ages, and genders. Unlike BMI, which may be less accurate for individuals with muscular builds or significant abdominal fat, WtHR provides a more focused measure of central obesity. It has been demonstrated as a reliable predictor of obesity-related health risks, such as cardiovascular disease and diabetes, in both adults and children. The consistent WtHR threshold of 0.5 for both adults and children simplifies epidemiological screening and personal health assessments across age groups, in contrast to BMI, where thresholds vary by age and require adjustment for physiological differences during growth and development. The uniform cutoff for WtHR, regardless of age, enhances its utility in clinical settings and public health surveillance, offering a straightforward, universally applicable metric for assessing obesity risk.

Key Explanatory Variables

To quantify the extent of Internet usage among Chinese citizens, this article focuses on two key metrics. The primary emphasis is on Internet usage as an explanatory variable. To this end, I create a dummy variable, where a value of 1 indicates Internet usage, and 0 indicates non-use. Additionally, the paper examines the average daily time spent online as another indicator of Internet usage. I define the amount of time spent online as the total number of hours Chinese citizens spend each day engaging in various online activities, including online education, social networking, information gathering, entertainment, and more. The

definitions of all variables used in my study are presented in Table 4.2.

4.6 Research Methods

4.6.1 Baseline Specification

We conduct separate regression analyses for adults and children since the control variables differ significantly for each demographic group. For example, children are not required to answer questions related to marital status or other topics more applicable to adults. Conducting separate analyses allows for more accurate and relevant modelling based on the distinct characteristics and backgrounds of each demographic group. Therefore, to formally test my hypothesis, I initially estimate the following models: Equation (4.1) pertains to adults, and Equation (4.2)

$$Overweight_{it}/Obesity_{it} = \beta_0 + \beta_1\ Internet_{it} + \gamma\ X_{it} + v_i + v_t + \varepsilon_{it}, \tag{4.1}$$

$$Overweight618_{it}/Obesity618_{it} = \beta_0 + \beta_1\ Internet_{it} + \gamma\ Z_{it} + v_i + v_t + \varepsilon_{it}, \tag{4.2}$$

where $Overweight_{it}$ and $Obesity_{it}$ represent whether Chinese resident i is obese or overweight at time t for adults, respectively. Similarly, $Overweight618_{it}$ and $Obesity618_{it}$ indicate whether Chinese resident i aged 6-18 is obese or overweight at time at time t, respectively. $Internet_{it}$ indicates Internet usage at time t. X_{it} and Z_{it} represent control variables specific to adults and children, respectively.[1] X_{it} includes personal characteristics such as age, gender, and marital status, as well as family and regional characteristics pertinent to adults. Z_{it} includes similar control variables tailored for children, such as age, education level, and parental characteristics, excluding marital status and other adult-specific factors. The error

[1]See Appendix C.1 for more details about the selection of control variables and their expected signs.

term includes v_i, which denotes individual unobserved heterogeneity. I take this component into account by using panel data estimators. v_t is a time-specific component of the error term, which I account for by including time dummies in all models. ε_{it} is the idiosyncratic component of the error term.

According to my hypothesis 1, I expect to observe positive and statistically significant β_1 coefficients in every regression of obesity and overweight probabilities.

4.6.2 Estimation Methodology

Given that my dependent variable is binary and I am working with a panel data set, I begin my analysis by applying a fixed-effects linear probability model (LPM). The LPM is straightforward and allows for the inclusion of fixed effects, which helps control for unobserved heterogeneity that may vary across individuals but remain constant over time. This is particularly useful in my context, where individual-specific characteristics might influence the outcome, and failing to account for these could lead to biased estimates.

We also employ the correlated random effects (CRE) probit estimator in the subsequent sub-section. The CRE approach was originally introduced by Mundlak (1978) for use with balanced panel data and later modified by Wooldridge (2019) to accommodate unbalanced panels. This model is preferred over the basic random-effects Probit model because it permits the correlation between unobserved heterogeneity and observed covariates. This is achieved by parameterising the error term's component in the primary model based on the time-averaged values of the time-varying variables. Essentially, this method involves estimating an enhanced version of the primary model, which incorporates these time averages, using a random-effects estimator.

4.6.3 Mechanisms

We aim to investigate the mechanisms through which Internet use may influence the probability of being overweight/obese among Chinese residents. Specifically, I explore six potential mechanisms: physical inactivity, sleep deprivation, alcohol intake, and the intake of energy, protein, fat, and carbohydrates.[2] To do this, I employ a mediation analysis using the Sobel test. First, I estimate the following equation to determine the impact of Internet use on each of the six mechanisms

$$Mechanism_{it} = \beta_1 + \pi Internet_{it} + \gamma_2 X_{it} + v_i + v_t + \varepsilon_{it}. \tag{4.3}$$

Next, I estimate the effect of each mechanism on the probability of being overweight/obese, controlling for Internet use

$$Overweight_{it}/Obesity_{it} = \beta_0 + \theta Mechanism_{i(j)t} + \gamma_1 X_{it} + v_i + v_t + \varepsilon_{it}, \tag{4.4}$$

where $Overweight_{it}/Obesity_{it}$ indicates whether Chinese residents i is overweight/obese at time t. $Internet_{it}$ represents the time spent on the Internet. $Mechanism_{i(j)t}$ represents mechanism j for Chinese resident i at time t. I consider seven mechanisms, namely physical inactivity, lack of sleep and alcohol, energy, protein, fat, and carbohydrate intake. The remaining variables in Equations (4.3) and (4.4) are identical to those in Equation (4.1).[3]

[2]The definitions of the mechanism variables are reported in Table C.2.

[3]Since questions about alcohol intake in the survey are only asked of individuals aged 12 and older, and there are also a large number of missing values for sleep duration and nutritional intake among children, my analysis of the mechanisms is focused solely on adults.

4.7 Empirical Results

4.7.1 Descriptive Statistics

Descriptive Statistics for the Whole Sample

Table 4.2 presents the descriptive statistics for the key variables used in this study. On average, 42.3% of respondents are classified as overweight, and 10.9% as obese. Among children aged 6 to 18 years, 20.9% are overweight, and 7.28% are obese. In terms of Internet usage, 23.8% of the sample uses the Internet, with an average daily usage time of 23.71 minutes. The table also includes descriptive statistics for the control variables, which are detailed in Appendix C.1.

Body Weight

We further explore differences in body weight across various population groups. Figure 4.2 shows the trend in mean BMI values by gender, household characteristics, and place of residence. The overall mean BMI for the sample is 22.92 kg/m^2, with an upward trend across all groups over the survey years. This rise in BMI across China can be attributed to rapid economic growth and urbanisation, leading to lifestyle changes such as increased consumption of high-calorie foods, more sedentary work environments, and decreased physical activity.

BMI values also vary by gender and place of residence. Males, urban residents, and those in northern regions consistently have higher BMI values compared to females, rural residents, and those in southern regions. These differences align with general observations. Rural populations typically engage in more physical labour, while the southern regions of China tend to have lighter diets with lower carbohydrate intake compared to the northern

regions.

Figure 4.3 illustrates the distribution of adult BMI density. According to the WHO standard for Asian adults (Organization, 2000), individuals with a BMI of 24 or above are considered overweight. The figure shows that approximately 40% of the sample falls into this category, which translates to over 500 million overweight adults in China.

Since BMI thresholds for overweight and obesity differ between adults and children, I apply specific thresholds for each group. Figure 4.4 highlights trends in overweight and obesity rates among adults and children from 2004 to 2015, with both groups showing a clear upward trajectory. The percentage of overweight adults increased from approximately 35% to 50%, while overweight rates for children grew from 18% to 23%. Similarly, adult obesity rates rose from 8% to 14%, and child obesity rates jumped from 2% to 10%, indicating a growing public health concern.

Internet Usage

As shown in Figure 4.5, Internet usage has been steadily increasing among the Chinese population. Men and urban residents show significantly higher levels of Internet usage compared to women and rural residents. Several factors can explain this disparity. Men tend to engage more with digital platforms for activities like gaming and entertainment, which are more accessible online. Moreover, urban areas generally have better infrastructure, including higher-quality Internet access and broader digital literacy, which facilitates easier adoption of digital technologies. In contrast, women and rural residents often face barriers such as limited digital education, restricted access to technology, and social or cultural norms that influence their lower levels of Internet use.

Figure 4.6 illustrates the consistent rise in average daily Internet usage across different

demographic groups in China from 2006 to 2015. Males consistently have higher Internet usage (red line) than females (green line), with a sharper increase over time. In 2006, both genders had relatively low average daily usage, just above 10 minutes. By 2015, males' average daily Internet usage had surged to around 45 minutes, while females reached approximately 35 minutes. This gender gap in Internet usage persisted throughout the period, reflecting differing engagement with online activities.

A pronounced urban-rural divide is also evident. Urban residents (grey line) consistently used the Internet more than rural residents (orange line). In 2006, urban individuals averaged around 15 minutes per day, while rural residents averaged just over 5 minutes. By 2015, urban residents' Internet use had risen to just under 50 minutes per day, while rural residents' usage increased to around 30 minutes, showing significant growth but still lagging behind urban users. The disparity between rural and urban Internet usage highlights ongoing challenges related to infrastructure and digital access, though the rapid growth in rural Internet use suggests improvements over time.

The overall Internet usage (blue line) for the entire population mirrors the upward trend across all subgroups, growing from just above 10 minutes per day in 2006 to almost 50 minutes by 2015. However, despite this overall increase, disparities in usage patterns—particularly in terms of gender and the rural-urban divide—underscore persistent inequalities in Internet access, driven by structural factors such as education, access to technology, and socio-economic conditions.

Table 4.1 also compares overweight and obesity rates between Internet users and non-users. The data shows that respondents who use the Internet have significantly higher rates of overweight and obesity. Among adults who do not use the Internet, 41.6% are overweight, and 10.8% are obese. These rates rise to 43% overweight and 11.1% obese among Internet users. A similar pattern is observed among adolescents, where 21.7% of Internet users are

overweight and 7.7% are obese, compared to 19.3% overweight and 6.9% obese among non-users. These differences are statistically significant at the 1% level.

4.7.2 Baseline Results

Linear Probability Fixed-Effects Estimates for Adults

We begin my analysis by presenting the fixed-effect linear probability estimates for the probability of being overweight and obese in Table 4.3. Column (1) shows that Internet usage significantly affects the probability of being overweight, with a coefficient of 0.015. This result means that Internet users are 1.8 percentage points more likely to be overweight than individuals who do not use the Internet. These effects are economically significant: for residents using the Internet, they correspond to an increase of 4.25% (0.018/0.423) in the mean value of overweight reported in Table 4.2. This result is consistent with most studies. (Bélanger et al., 2011; Vandelanotte et al., 2009).

Internet use significantly increases the likelihood of being overweight, which may be due to several interrelated factors. First, Internet use fosters sedentary behaviour, as individuals spend more time on activities such as browsing, streaming, and engaging with social media, thereby reducing opportunities for physical exercise and overall energy expenditure. This shift from active to passive pursuits directly contributes to weight gain over time. Second, Internet use can adversely affect dietary habits and food consumption patterns. The pervasive exposure to online advertising, particularly for high-calorie, nutrient-poor foods, influences food preferences and encourages the consumption of unhealthy snacks and meals. Additionally, the convenience of online food delivery services exacerbates the problem by providing easy access to calorie-dense options, often leading to overeating and poor nutritional choices. Internet use can also disrupt regular eating patterns, as individuals may eat

while distracted or outside of regular mealtimes, leading to overeating and a lack of awareness about portion sizes, further contributing to weight gain. Finally, excessive Internet use, particularly at night, can disrupt sleep patterns, leading to poor sleep quality and shorter sleep duration. Inadequate sleep is closely linked to weight gain and obesity, as it affects hormones that regulate hunger and appetite, often resulting in increased consumption of calorie-dense foods.

In my analysis, while Internet use is significantly associated with being overweight, it does not show a statistically significant effect on obesity. This suggests that Internet use may contribute to initial weight gain but is insufficient on its own to lead to obesity, a condition that involves more complex factors such as prolonged caloric excess, genetic predispositions, and metabolic conditions. The absence of significance may reflect a threshold effect, where the impact of Internet use influences weight gain but not the more extreme condition of obesity.

In terms of control variables, I observe that the effects on overweight and obesity are consistent with both the literature and my predictions. Compared with illiterates, people with a college degree have a lower probability of being overweight (Column 1) and obese (Column 3). This is consistent with the findings of Dursun et al. (2018), who also reported that higher educational attainment is associated with healthier weight outcomes, likely due to better health literacy, access to resources, and healthier lifestyle choices among the more educated population. Additionally, consistent with the study by Jolliffe (2011), income level has a significant effect on overweight (Column 1) and obesity (Column 3). Specifically, people with higher incomes have a lower probability of being overweight and obese. This relationship can be attributed to the fact that higher income provides greater access to healthier food options, fitness facilities, and healthcare, all of which contribute to maintaining a healthy weight. Moreover, individuals with higher incomes are often more likely to engage in regular physical activity and have better overall health awareness, further reducing the likelihood of

overweight and obesity.

Linear Probability Fixed-Effects Estimates for Children

The subsequent analysis examines the impact of Internet usage on overweight and obesity rates among Chinese children aged 6 to 18. In refining my approach, I adjust for variables that are particularly pertinent to this age group rather than adults. Notably, instead of focusing on marital status and the highest educational degree, I consider the educational levels of the parents. This adjustment allows us to employ a set of control variables specifically tailored for my regression models. The results of the fixed effects linear probability estimation, which details the effects of Internet usage on childhood overweight and obesity, are presented in Table 4.4. Column (1) reveals that Internet use is associated with a coefficient of 0.029, which is statistically significant at the 5% level. This result implies that children who use the Internet have a 2.9 percentage point higher probability of being overweight compared to those who do not use the Internet.

In addition to factors typically associated with adults, such as sedentary behaviour and consumption of high-calorie foods, children face unique challenges that heighten their vulnerability to overweight and obesity. Children are in a crucial phase of growth and development, making them particularly sensitive to changes in energy balance. Sedentary behaviour, often linked to excessive Internet use, can lead to rapid weight gain in this age group. Moreover, children's still-developing self-regulation skills predispose them to overindulgence in online activities, resulting in prolonged periods of inactivity and unhealthy eating patterns. Additionally, children are highly susceptible to peer pressure and the influence of social media, which can further promote unhealthy lifestyle choices and intensify the impact of Internet use on their weight management.

We observe that the relationship between Internet usage and obesity, similar to the

findings for adults, is not statistically significant (Column 3). In addition to the reasons previously discussed, this lack of significance may also be due to the subtle effects of Internet use being too small to detect statistically in relation to obesity, particularly given the relatively low proportion of individuals classified as obese within the sample.

Verifying Whether the Results Are Robust to Using a Correlated Random Effects Probit Estimator

Columns (2) and (4) of Tables 4.3 and 4.4 present the CRE estimates for the probability of overweight/obesity among Chinese adults and children, respectively. I initially use a linear fixed effects model because it effectively controls for unobservable individual heterogeneity, reducing bias from omitted variables. However, given that my dependent variable is binary, the linear fixed effects model has certain limitations, such as potentially producing predicted values that fall outside the range of 0 and 1, which are not meaningful in a probabilistic context. To test the robustness of my results, I also utilised the CRE Probit Estimator. This method is more suitable for handling binary dependent variables, as it can account for individual heterogeneity while providing more accurate probability estimates in discrete choice models.

We observe consistent results with previous findings, where Internet use is significantly associated with a higher probability of being overweight and shows a weaker, non-significant association with obesity in both adults and children. Specifically, in Column (2) of Table 4.3, Internet use increases the probability of being overweight among adults by 1.3 percentage points, while in Table 4.4, Column (2), it increases the probability by 4 percentage points among children. For obesity, as shown in Column (4) of both tables, the results indicate a weaker and non-significant association, suggesting that while Internet use contributes to being overweight, its direct impact on obesity is less pronounced. These findings confirm the

robustness of my results across different estimation techniques.

4.7.3 Heterogeneity Analysis

Heterogeneity by Gender

Table 4.5 presents the results of my heterogeneity analysis by gender, examining the impact of Internet use on overweight and obesity among Chinese adults and children. Panel A focuses on adults, where Internet use is associated with a 1.5 percentage point increase in the probability of being overweight among males (Column 1). In contrast, the effect for females is smaller and not statistically significant (Column 2). When it comes to obesity, Internet use does not have a significant impact on either gender, as shown by the non-significant coefficients in Columns (3) and (4). In panel B, which analyses children aged 6-18, the impact of Internet use is more pronounced, particularly among males. Column (1) indicates that boys have a 9.5 percentage point higher likelihood of being overweight due to Internet use. Additionally, male children exhibit a significant 6.5 percentage point increase in the probability of being obese (Column 3). In contrast, the effect of Internet use on both overweight and obesity among female children is smaller and not statistically significant, as reflected in Columns (2) and (4). my findings support the hypothesis (H2) that the association between Internet use and overweight/obesity among Chinese residents is stronger in males than in females.

The comparison between males and females across both adults and children reveals that males are more affected by Internet use in terms of weight gain. This difference may be attributed to a combination of behavioural and biological factors, where males might engage more frequently in sedentary activities or have different metabolic responses to prolonged Internet use. Furthermore, societal and cultural norms could influence Internet usage pat-

terns, with males potentially being more inclined toward activities that promote sedentary behaviour, such as gaming, which may lead to a greater impact on their weight.

Heterogeneity by Regions

Table 4.6 presents the results of my heterogeneity analysis by region, focusing on the impact of Internet use on overweight and obesity among Chinese adults and children aged 6-18, with distinctions between rural and urban areas. For adults (Panel A), Internet use significantly increases the likelihood of being overweight in rural areas by 2.1 percentage points (Column 1), while in urban areas, the effect is smaller and not statistically significant (Column 2). This conclusion supports my hypothesis (H3).

In children aged 6-18 (Panel B), the impact of Internet use is more pronounced in urban areas, where it leads to a 16.5 percentage point increase in the likelihood of being overweight (Column 1), whereas in rural areas, the effect is not significant (Column 2). This difference can be attributed to disparities in Internet accessibility. Urban children enjoy significantly greater access to the Internet compared to their rural counterparts. In particular, during the survey period, rural children faced limited access to reliable Internet resources, resulting in significantly more restricted Internet use compared to urban children. Urban children may also face higher academic pressures leading to prolonged periods of sedentary behaviour, such as studying and using computers, which, when combined with Internet use, contributes significantly to the risk of being overweight. As with the main results, I do not observe any effect of Internet use on obesity.

Overall, my findings partially support the hypothesis (H3) that the association between Internet use and overweight/obesity among Chinese adults is stronger in urban areas than in rural areas but not among children.

4.7.4 Robustness Tests

We conduct a series of robustness checks to confirm the main results.

IV Estimates for the Probability of Being overweight/obese

To address potential endogeneity concerns in the relationship between Internet use and the probability of being overweight or obese, I employ an instrumental variables (IV) approach using a fixed-effects model. The use of IV estimation is crucial in this context as it helps to mitigate bias that could arise from reverse causality or omitted variable bias, which might otherwise confound the estimated effects of Internet use on obesity and overweight. In my model, I use *Internet_comm* as an instrumental variable, representing the community-level availability of Internet infrastructure. This variable meets the two key conditions for a valid instrument. First, it is relevant as the availability of Internet infrastructure at the community level is strongly correlated with individual Internet usage: places with better Internet infrastructure are likely also to have higher rates of Internet use by their residents. Second, *Internet_comm* is plausibly exogenous to individual health outcomes such as obesity or being overweight: community-level availability of Internet infrastructure results from broader economic and policy factors, which are unlikely to vary with the individual-level characteristics or health behaviours of a resident. This exogeneity assumption ensures that *Internet_comm* influences health outcomes only indirectly through its effect on Internet usage, and not through other channels that directly affect obesity or overweight.

The first stage results, reported in Column (1) of Table 4.7, confirm the relevance of my instrument. The coefficient for *Internet_comm* is highly significant, indicating a strong relationship between community-level Internet infrastructure and individual Internet use. The first stage results, reported in Column (1) of Table 4.7, confirm the relevance and strength of

my instrument. The coefficient for *Internet_comm* is highly significant, indicating a strong relationship between community-level Internet infrastructure and individual Internet use. The Kleibergen-Paap rk Wald F-statistic, with a value of 47.32, is well above the conventional threshold of 10 and exceeds the critical value for a maximum of 10% bias(Stock and Yogo, 2005), confirming the strength and validity of my instrument. In the second stage, as shown in Columns (2) and (3), I find that Internet use is significantly associated with a higher probability of being overweight and obese. Specifically, the IV estimates indicate that Internet use increases the probability of being overweight by 2.03 percentage points and the probability of being obese by 1.40 percentage points. These results are consistent with my baseline fixed-effects estimates, which also suggested a positive association between Internet use and the likelihood of being overweight or obese. Overall, the consistency between the IV and baseline results suggests that my original findings are not driven by endogeneity, further solidifying the robustness of my conclusions.

Alternative Measurements of Body Weight and Internet Usage

We explore two additional weight measurement methods, namely BMI and WtHR, and replicate the baseline regression. Panel A in Table 4.8 shows that Internet use is associated with an increase in BMI among Chinese residents, with an average rise of 0.113 kg/m^2. This effect is stronger among males (0.142 kg/m^2) and urban residents (0.145 kg/m^2), suggesting that Internet use may contribute to higher body weight, particularly in these subgroups. In Panel B, the results show a significant positive association between Internet use and children's BMI in the overall sample, with a stronger effect observed in urban areas and among male children. Specifically, the coefficient for the full sample is 0.175, and for males, it is 0.181, both significant at the 1% level. However, the relationship is not statistically significant for female or rural children. These findings are consistent with the baseline results.

Table 4.9 extends the analysis to central obesity,[4] revealing that Internet use significantly increases the probability of central obesity among women (4.7 percentage points) and urban residents (3.4 percentage points). Interestingly, while BMI increases with Internet use for both men and women, central obesity is significant only for women. This difference may be due to gender-specific fat distribution, with women more likely to accumulate abdominal fat, making them more susceptible to central obesity. Conversely, while Internet use leads to significant obesity in men, it does not have the same effect on central obesity, likely due to a more uniform fat distribution in men. These findings broadly align with the baseline results but highlight important gender differences in how Internet use affects body weight and fat distribution.

To further explore the impact of Internet usage, I replace the binary indicator with a continuous variable representing the average time spent online. This allows for a more nuanced understanding of how varying levels of Internet engagement influence outcomes. The results, as shown in Table 4.10, indicate that while the time spent online is significantly associated with an increased likelihood of being overweight, it does not have a statistically significant effect on obesity. This aligns with my baseline results, which also show a stronger link between Internet use and overweight. Specifically, each additional minute of daily Internet use is associated with a 0.01 percentage point increase in the probability of adult overweight (Column 1) and a 0.08 percentage point increase in child overweight (Column 3).

Controlling for Dietary Quality

To better understand the relationship between Internet use and weight outcomes, it is crucial to account for dietary quality, a significant determinant of body weight. Research demonstrates that individuals with higher diet quality scores are less likely to gain weight over

[4]Due to the high number of missing values in children's reported waist circumference, I focus solely on adults in the central obesity regression.

time compared to those with poorer diet quality (Barnes et al., 2016). I employ a dummy variable to indicate whether an individual's daily diet adheres to the recommended intake, as detailed in Table C.3. According to Table 4.11, even after adjusting for dietary quality, Internet use continues to be significantly linked with an increased likelihood of being overweight. Specifically, Column (1) reveals that Internet use corresponds to a 1.2 percentage point rise in the probability of being overweight among adults, a finding that retains statistical significance after controlling for diet. For children, Internet use is associated with an 8.4 percentage point increase in the likelihood of being overweight, as shown in Column (3). It is also pertinent to highlight that the associations with obesity were not statistically significant. These results align with my initial findings, indicating that while Internet use significantly affects overweight rates, its impact on obesity is less pronounced. Additionally, the findings affirm that a healthy diet diminishes the risk of both overweight and obesity, underscoring the critical role of dietary quality in moderating the effects of Internet use on weight outcomes.

4.7.5 Mechanisms

The Role of Physical Inactivity, Frequent Drinking, and Sleep Deprivation

Table 4.12 presents the results of my mechanisms analysis examining the relationship between Internet use and overweight among Chinese residents, focusing on the mediating effects of physical inactivity, frequent drinking, and sleep deprivation. Panel A shows the direct effects of Internet use on these three potential mechanisms, while Panel B examines how these mechanisms contribute to the likelihood of being overweight.

In Panel A, I see that Internet use is positively associated with physical inactivity, frequent drinking, and sleep deprivation. The coefficient for physical inactivity is 0.043

(Column 1), and for frequent drinking is 0.055 (Column 2), both statistically significant at the 1% level, indicating that Internet users are more likely to be physically inactive and engage in frequent drinking. Additionally, Internet use increases the likelihood of sleep deprivation, with a coefficient of 0.049 (Column 3), statistically significant at the 5% level. These results suggest that Internet use may contribute to overweight through its effects on physical inactivity, increased alcohol consumption, and poor sleep quality.

In addition, I examine the extent to which Internet use affects overweight by controlling for these three moderating variables. In Panel B, the coefficient for Internet use on overweight remains significant, but it is reduced compared to the original coefficient of 0.018 in Column (1) of Table 4.12, which is estimated without these moderating variables. In Column (1), when physical inactivity is included as a control variable, the coefficient for Internet use on overweight decreases from the original 0.018 to 0.015, representing a 16.7% reduction. This suggests that reduced physical activity significantly mediates the relationship between Internet use and overweight. In Column (2), the coefficient for Internet use remains significant at 0.015. However, the effect of frequent drinking on overweight is not statistically significant. This suggests that while Internet use is associated with frequent drinking, this behaviour may not be a primary pathway through which Internet use leads to being overweight. In Column (3), controlling for sleep deprivation reduces the coefficient to 0.014, a 22.2% decrease, highlighting that poor sleep also plays a role in mediating the impact of Internet use on overweight. Sobel tests (Sobel, 1982) reject the null hypothesis of no mediation effects, which further confirms these findings, showing that Internet use plays a key role in contributing to being overweight as it can enhance the risk of being overweight through physical inactivity and sleep deprivation, not alcohol intake.

The Role of Nutrients Intake

In robustness tests, I control for dietary quality and find that a healthy diet reduces the likelihood of being overweight and obese, emphasising the importance of diet quality in moderating the impact of Internet use on body weight. However, to further understand how Internet use specifically affects body weight, I analyze its influence on the intake of specific nutrients, namely energy, fat, carbohydrates, and protein. While the importance of overall diet quality is established, examining the intake of these individual nutrients allows us to more clearly understand the specific mechanisms through which Internet use contributes to weight gain.

Table 4.13 presents my analysis of how different nutrient intakes mediate the relationship between Internet use and overweight among Chinese residents. Panel A shows that Internet use is associated with significant increases in energy (Column 1) and fat intake (Column 2). At the same time, it decreases carbohydrate intake (Column 3) with no significant effect on protein intake (Column 4). In Panel B, I examine how these changes in nutrient intake influence the likelihood of being overweight. Controlling for energy intake in Column (1) reduces the coefficient of Internet use on overweight to 0.009, indicating that increased energy consumption partially mediates the relationship. Similarly, controlling for fat intake in Column (2) reduces the coefficient to 0.010, showing that higher fat intake also mediates this effect. The Sobel test Z confirm the significance of these mediation effects. In contrast, controlling for carbohydrate intake in Column (3) and protein intake in Column (4) results in non-significant mediation effects, as indicated by the Sobel test results. These findings highlight the significant role of energy and fat intake in mediating the impact of Internet use on overweight.

The mechanisms analysis reveals that Internet use contributes to overweight among Chinese residents primarily through increased physical inactivity, sleep deprivation, and

higher intake of energy and fat. Physical inactivity and sleep deprivation significantly mediate the relationship between Internet use and overweight, with a 16.7% and 22.2% reduction in the coefficient for Internet use on overweight, respectively. While Internet use is associated with frequent drinking, this behaviour does not significantly mediate the effect on overweight. Regarding nutrient intake, Internet use leads to higher energy and fat consumption, both of which significantly mediate the impact on overweight, while changes in carbohydrate and protein intake do not have a notable mediation effect. Sobel tests confirm the significance of these mediation pathways, emphasising that physical inactivity, sleep deprivation, and increased energy and fat intake are the primary ways through which Internet use influences weight gain. Figure 4.7 clearly shows the results of my mechanism analysis.

4.8 Conclusion, Policy Implications, and Future Research

This study investigates the relationship between Internet usage and overweight/obesity among Chinese residents, leveraging data from multiple waves of the CHNS. My analysis reveals a significant positive correlation between Internet use and the likelihood of being overweight or obese. Specifically, Chinese adults (children) who use the Internet are 1.8 (7.9) percentage points more likely to be overweight than those who do not use it. This association is particularly pronounced among children.

Given these findings, it is crucial to acknowledge the pathways through which Internet use influences weight gain. I identify three primary mechanisms: Increased intake of unhealthy foods, physical inactivity due to sedentary Internet activities, and sleep deprivation, all of which contribute to the rising rates of overweight and obesity. These insights provide important contributions to the existing literature by deepening my understanding of how digital behaviours influence health outcomes in China, a context with rapidly increasing

Internet penetration.

Our results have important policy implications. First, there is a clear need for the government to implement stricter regulations on online advertising, especially for junk food, and to monitor Internet cafés more closely. Additionally, encouraging healthier digital behaviours through targeted public health campaigns can mitigate the negative effects of excessive Internet use. For instance, Tencent's implementation of a juvenile model that allows parents to supervise their children's Internet use represents a positive step forward. Expanding such measures to promote responsible Internet usage for minors could further protect vulnerable groups from the associated risks of obesity.

For children in particular, I recommend that parents actively oversee their Internet usage and encourage responsible behaviour online. Government initiatives should also focus on regulating minors' Internet access while promoting constructive digital habits. Moreover, physical activity must be encouraged through the construction of public venues and facilities designed to engage citizens in exercise. Nutritional literacy campaigns could play an equally important role in counteracting unhealthy dietary patterns linked to sedentary lifestyles.

Despite these contributions, this study is not without limitations. Internet usage is rapidly evolving, and my study captures only a snapshot of this dynamic landscape. Additionally, while I control for several confounding factors, unobserved variables may still influence my results. Nonetheless, the findings highlight the critical importance of addressing the health risks associated with Internet usage, particularly in a highly connected society like China.

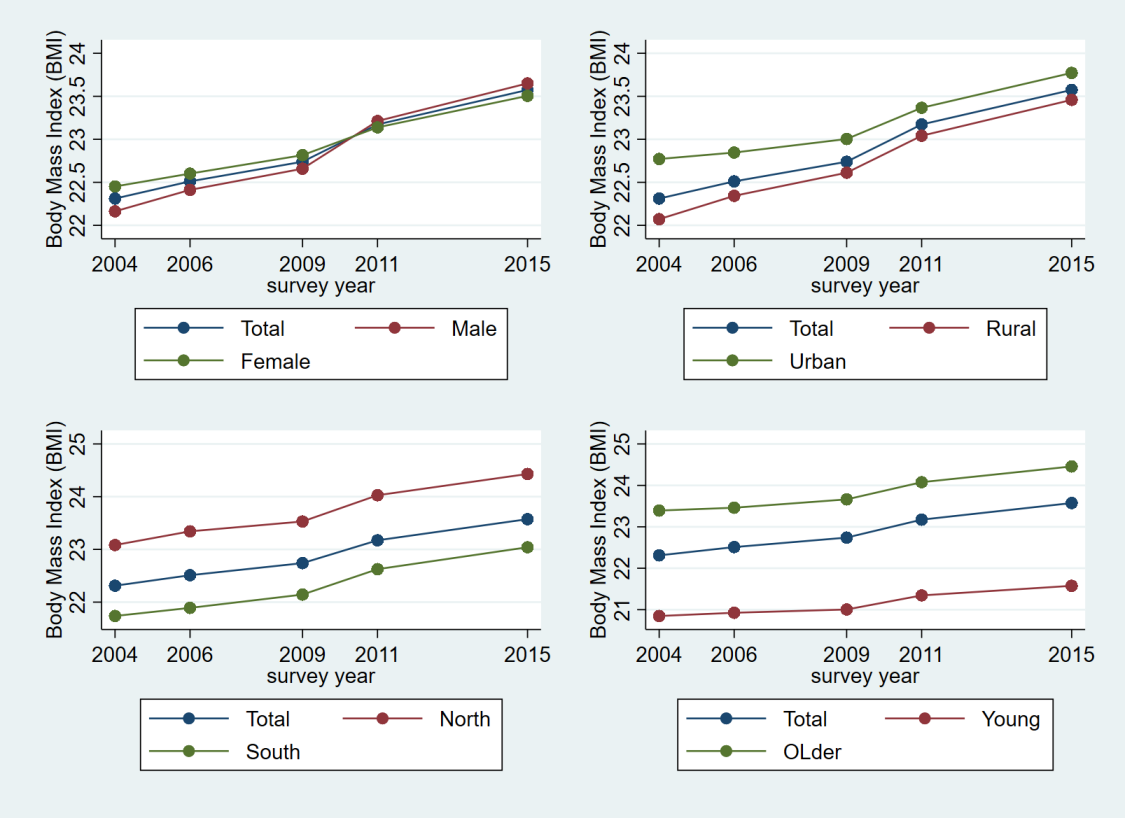
Figures and Tables for Chapter 4

Figure 4.1: Provinces and municipalities covered by the CHNS survey in China



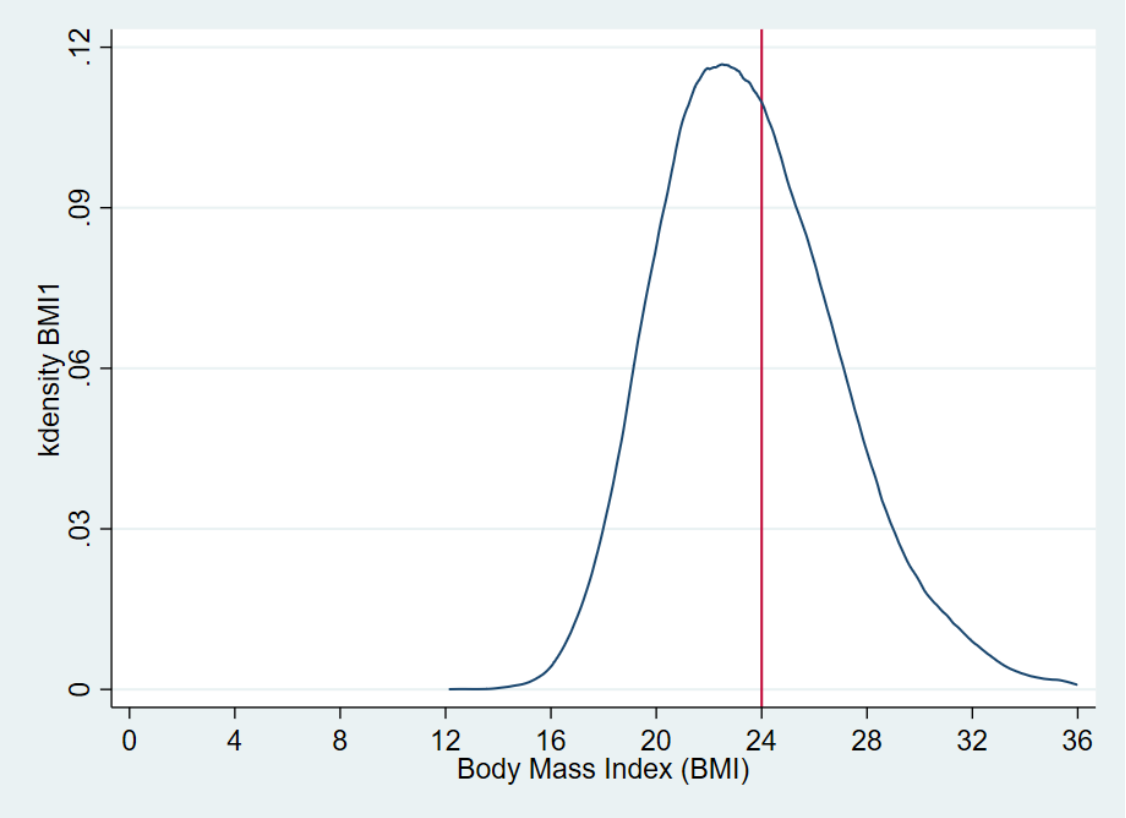
Source: China Health and Nutrition Survey.

Figure 4.2: Trends in BMI across demographic groups in China (2004-2015)



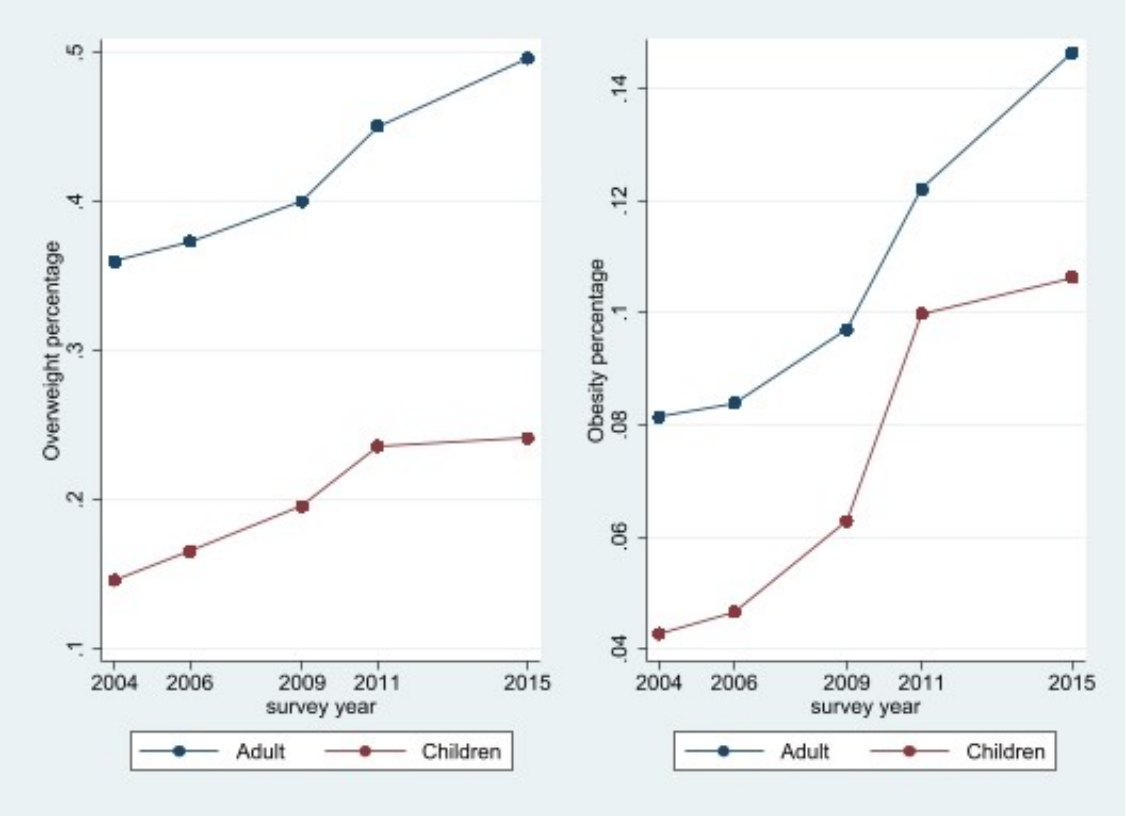
Note: The data is based on my main regression sample, which includes all respondents aged 6 to 80 from 2004 to 2015.
Source: Authors' calculations based on the CHNS.

Figure 4.3: Kernel density estimate of BMI distribution with overweight threshold



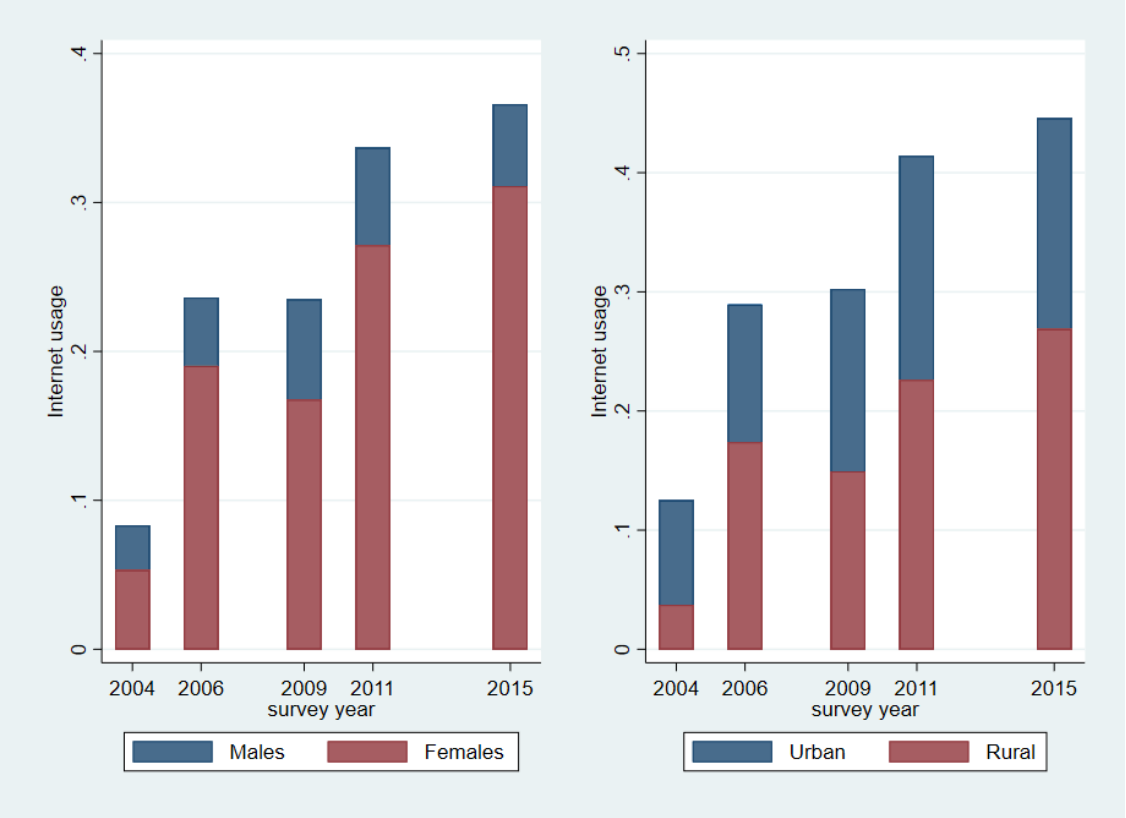
Note: The data is based on my main regression sample, which includes adult respondents aged 18 to 80 from 2004 to 2015.
Source: Authors' calculations based on the CHNS.

Figure 4.4: Trends in overweight and obesity percentages by adults and children (2004-2015)



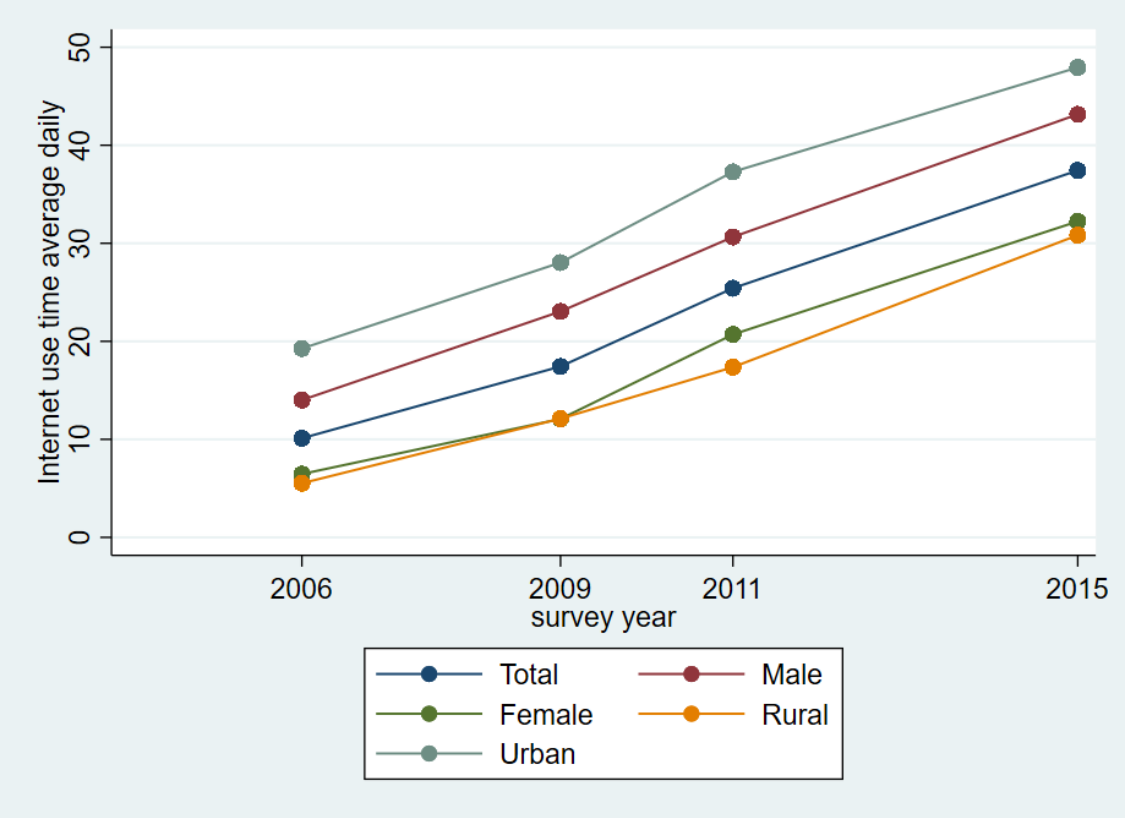
Note: The data is based on my main regression sample, which includes all respondents aged 18 to 80 from 2004 to 2015.
Source: Authors' calculations based on the CHNS.

Figure 4.5: Trends in Internet usage by gender and urban-rural residence (2004-2015)



Note: The data is based on my main regression sample, which includes all respondents aged 18 to 80 from 2004 to 2015.
Source: Authors' calculations based on the CHNS.

Figure 4.6: Trends in average daily time spent online by demographic groups (2004-2015)



Note: The data is based on my main regression sample, which includes all respondents aged 18 to 80 from 2004 to 2015.
Source: Authors' calculations based on the CHNS.

Figure 4.7: Results of mechanism analysis

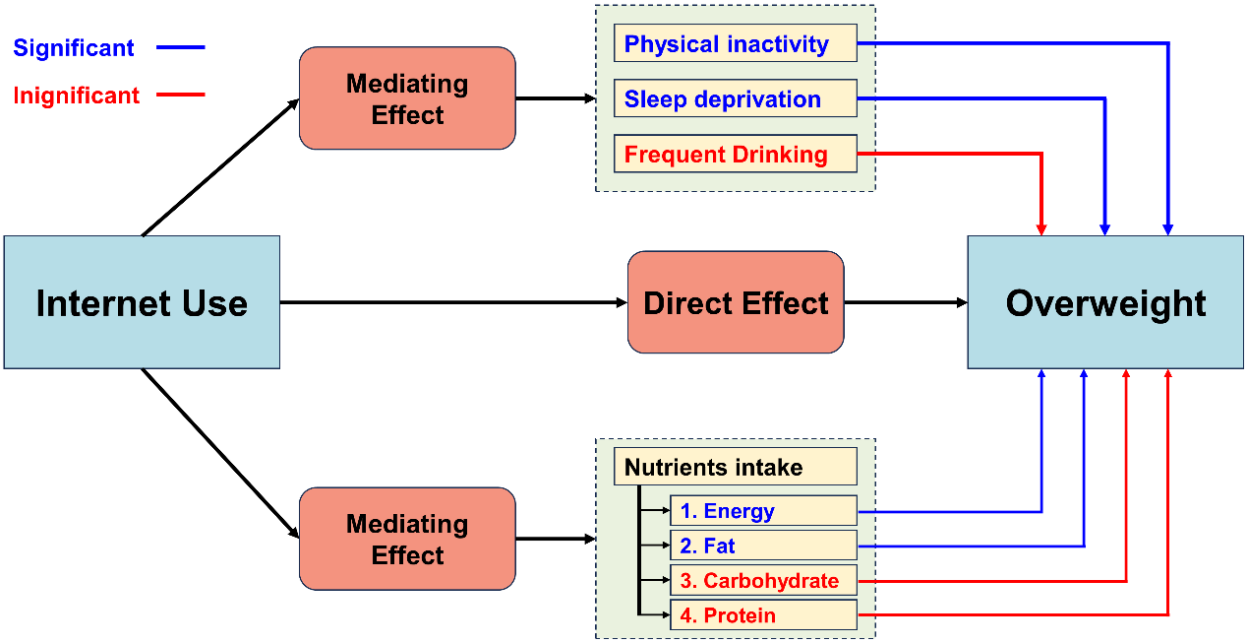


Table 4.1: Descriptive statistics

VARIABLES	(1) N	(2) Mean	(3) SD	(4) Min	(5) Max
Dependent Variables					
BMI	50,163	22.92	3.898	12.40	36.69
Overweight	46,827	0.423	0.494	0	1
Obesity	46,827	0.109	0.312	0	1
Overweight618	3,309	0.209	0.407	0	1
Obesity618	3,309	0.0728	0.260	0	1
Central obesity	46,648	0.511	0.500	0	1
Independent Variables					
Internet	46,827	0.238	0.426	0	1
Internet time	38,593	23.71	60.76	0	450
Control Variables					
Age	50,136	44.27	18.68	6	80
Gender	50,136	0.485	0.500	0	1
Married	46,827	0.844	0.363	0	1
Never married	46,827	0.0757	0.265	0	1
Divorced	46,827	0.0129	0.113	0	1
Widowed	46,827	0.0637	0.244	0	1
Elementary	46,827	0.202	0.402	0	1
Middle school	46,827	0.328	0.469	0	1
High school	46,827	0.203	0.402	0	1
College	46,827	0.0812	0.273	0	1

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Table 4.1 – continued from previous page

VARIABLES	N	Mean	SD	Min	Max
Edu Child	3,309	0.574	0.494	0	1
Edu father	3,309	0.667	0.471	0	1
Edu mother	3,309	0.507	0.499	0	1
Hhincome	50,136	13,433	12,855	0	59,176
Lnhhincome	50,136	9.037	1.141	0.0522	10.99
Health	50,136	0.144	0.351	0	1
Insurance	50,136	0.738	0.440	0	1
Phyact	50,136	0.148	0.355	0	1
Employed	46,827	0.565	0.496	0	1
Chronic	46,827	0.144	0.351	0	1
HBP	46,827	0.117	0.321	0	1
Diabetes	46,827	0.0280	0.165	0	1
Myocardial	46,827	0.0070	0.083	0	1
Apoplexy	46,827	0.0123	0.110	0	1
Smoke_ever	46,827	0.288	0.453	0	1

Note: The descriptive statistics for all variables are derived from the sample used to estimate equations (4.1) *and* (4.2) *in the main results. The total number of observations for Equation* (4.1) *is 12,196, and for Equation* (4.2) *it is 3,309.*

Table 4.2: Descriptive statistics of outcome variables for respondents who use and do not use the Internet

VARIABLES	Internet = 0					Internet = 1					Sign. Diff
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Mean	SE	Min	Max	Obs	Mean	SE	Min	Max	Obs	
Overweight	0.416	0.002	0	1	36,056	0.430	0.004	0	1	10,771	***
Obesity	0.108	0.001	0	1	36,056	0.111	0.002	0	1	10,771	***
Overweight618	0.193	0.006	0	1	2,099	0.217	0.010	0	1	1,210	***
Obesity618	0.069	0.004	0	1	2,099	0.077	0.006	0	1	1,210	***

*Notes: Columns 1–5 (6–10) report the statistics of the outcome variables for respondents who do not use (use) the Internet. Column (11) reports Wald t-tests for the differences in the means of the outcome variables between respondents who use the Internet and those who do not. SE denotes standard errors. Definitions of all variables are provided in Table C.1. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.*

Table 4.3: The estimates for the probability of being overweight/obese for adults

VARIABLES	Overweight		Obese	
	(1)	(2)	(3)	(4)
	Linear FE	CRE Probit	Linear FE	CRE Probit
Internet	0.018**	0.013**	0.006	0.003
	(2.21)	(1.98)	(1.26)	(1.23)
Age	0.020*	0.004	0.008	0.011
	(1.91)	(0.36)	(1.49)	(0.86)
Male		0.410***		0.157**
		(6.29)		(2.08)
Married	-0.064**	-0.041***	-0.039*	-0.057**
	(-2.29)	(-6.29)	(-1.43)	(-2.08)
Never married	0.135***	0.008***	0.013	0.081
	(4.19)	(3.88)	(0.45)	(0.21)
Divorced	-0.059	-0.015	0.025	0.019
	(-1.62)	(-1.42)	(0.85)	(0.68)
Widowed	-0.065**	-0.054**	0.023	0.043
	(-2.10)	(-2.51)	(0.83)	(0.91)
Elementary	-0.003	-0.0002	-0.008	-0.003**
	(-0.04)	(-0.75)	(-0.27)	(-1.97)
Middle school	-0.001	-0.001	-0.011	0.007**
	(-0.02)	(-0.14)	(-0.39)	(1.97)
High school	-0.007	-0.005	-0.009	-0.355*
	(0.11)	(0.23)	(-0.32)	(-1.98)
College	-0.002*	-0.004**	-0.003**	-0.003**
	(-2.03)	(-2.50)	(-2.11)	(-1.97)
Lnhhincome	-0.227**	-0.486***	-0.198*	-0.189***
	(-4.51)	(-5.58)	(2.98)	(-3.53)
Employed	-0.005	0.305***	-0.003	0.152

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VARIABLES	**Linear FE**	**CRE Probit**	**Linear FE**	**CRE Probit**
	(-0.92)	(3.85)	(-0.97)	(1.52)
Insurance	-0.023***	-0.018***	0.009**	0.002
	(-3.85)	(-4.36)	(2.41)	(0.18)
Health	-0.001	-0.005*	-0.004	-0.000
	(-0.11)	(-1.84)	(-1.06)	(-0.06)
HBP	0.019**	0.012***	0.027***	0.012*
	(2.46)	(5.46)	(4.21)	(2.17)
Diabetes	-0.043***	-0.019***	-0.042***	-0.026*
	(-2.62)	(-3.72)	(-2.71)	(-1.89)
Myocardial	0.001	0.001	-0.032	-0.022
	(0.04)	(0.04)	(-1.51)	(-1.16)
Apoplexy	-0.043**	-0.028**	0.003	0.002
	(-1.97)	(-2.99)	(0.16)	(0.09)
Ever smoke	-0.013	-0.008	-0.004	-0.001
	(-1.64)	(-1.89)	(-0.69)	(-0.88)
Phyact	-0.002*	-0.007***	-0.010*	-0.008
	(-0.34)	(-6.41)	(-1.93)	(-1.12)
Constant	-0.447	-0.254*	-0.310	-0.187
	(-0.95)	(-2.62)	(-1.25)	(-1.07)
Observations	46,827	46,827	46,827	46,827
R-squared	0.023	0.023	0.014	0.014
Number of id	19,922	19,922	19,922	19,922

*Notes: This table reports coefficients obtained using a fixed-effects linear estimator (Columns 1 and 3) and marginal effects obtained using a CRE Probit model (Columns 2 and 4). T-statistics calculated using standard errors clustered at the individual level are in parentheses. Time dummies and means of time-varying variables are included in the models but not reported for brevity. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

Table 4.4: The estimates for the probability of being overweight/obese for children

VARIABLES	Overweight618		Obese618	
	(1)	(2)	(3)	(4)
	Linear FE	CRE Probit	Linear FE	CRE Probit
Internet	0.029**	0.04**	-0.004	0.009*
	(1.68)	(2.26)	(-0.17)	(1.86)
Age	0.081*	0.071***	0.005	0.157***
	(1.89)	(4.78)	(0.16)	(3.28)
Male		0.224**		0.272*
		(2.09)		(1.87)
Edu	0.038	-0.024**	0.019	0.002*
	(0.98)	(2.09)	(0.67)	(1.87)
Edu_f	-0.129**	-0.176	-0.066*	-0.047
	(-2.44)	(-0.99)	(-1.71)	(-1.42)
Edu_m	-0.165***	-0.084	-0.041	-0.259
	(-3.16)	(-0.33)	(-1.20)	(-0.78)
Insurance	0.030	-0.027	0.000	-0.001
	(0.96)	(-1.12)	(0.01)	(-0.06)
Health	-0.088**	-0.067*	-0.018	-0.009
	(-2.38)	(-2.12)	(-0.66)	(-0.44)
Phyact	-0.008	-0.000	0.007	-0.127
	(-0.34)	(-0.12)	(0.39)	(-0.48)
Lnhhincome	-0.022	-0.013	-0.013	-0.059
	(-1.53)	(-1.13)	(-1.37)	(-1.30)
Constant	-0.426	-0.134	-0.009	-4.793***
	(-1.40)	(-1.34)	(-0.04)	(-7.02)
Observations	3,309	3,309	3,309	3,309
R-squared	0.103	0.103	0.033	0.033
Number of id	2,394	2,394	2,394	2,394

Notes: This table reports coefficients obtained using a fixed-effects linear estimator (Column

*1,3) and marginal effects obtained using a CRE Probit model (Column 2,4). The means of time-varying variables in the correlated random effects model are included in all models, but their coefficients/marginal effects are not reported for brevity. Time dummies are also included in all models, but their coefficients/marginal effects are also not reported for brevity. The dependent variables in Columns (1) and (3) represent the probability of being overweight, while those in Columns (2) and (4) represent the probability of being obese. Data from the 2004 to 2015 waves of the CHNS were used in estimation. T-statistics calculated using standard errors clustered at the individual level are in parentheses. The definitions of all variables are provided in Table C.1. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

Table 4.5: Heterogeneous effects of Internet usage based on gender

VARIABLES	**Overweight**		**Obese**	
	(1) Male	**(2) Female**	**(3) Male**	**(4) Female**
Panel A: Adults				
Internet	0.019**	0.013	0.009	0.002
	(2.65)	(1.37)	(1.38)	(0.36)
Control variables	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	22,263	24,564	22,263	24,564
Number of id	9,488	10,434	9,488	10,434
VARIABLES	**Overweight618**		**Obese618**	
	(1) Male	**(2) Female**	**(3) Male**	**(4) Female**
Panel B: Children				
Internet	0.035**	0.016	0.065**	0.054
	(2.31)	(1.13)	(1.97)	(1.55)
Control variables	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	1,380	1,178	1,380	1,178
Number of id	1,002	893	1,002	893

*Notes: This table reports coefficients obtained using a fixed-effects linear estimator. Time dummies are included in all models, but their coefficients are not reported for brevity. In Panel A, the dependent variable represents the probability of adult overweight (Columns 1-2) and adult obesity (Columns 3-4). In Panel B, it represents the probability of child overweight (Columns 1-2) and child obesity (Columns 3-4). Data from the 2004 to 2015 waves of the CHNS were used in estimation. T-statistics calculated using standard errors clustered at the individual level are in parentheses. The definitions of all variables are provided in Table C.1. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

Table 4.6: Heterogeneous effects of Internet usage based on region

VARIABLES	Overweight		Obese	
	(1) Rural	(2) Urban	(3) Rural	(4) Urban
Panel A: Adults				
Internet	0.021**	0.009	0.005	0.008
	(2.41)	(0.83)	(0.80)	(1.08)
Control variables	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	29,427	17,400	29,427	17,400
Number of id	11,710	8,212	11,710	8,212
VARIABLES	**Overweight618**		**Obese618**	
	(1) Rural	**(2) Urban**	**(3) Rural**	**(4) Urban**
Panel B: Children				
Internet	0.038	0.165***	0.004	0.065
	(1.07)	(2.85)	(0.17)	(1.38)
Control variables	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	1,646	912	1,646	912
Number of id	1,199	696	1,199	696

*Notes: This table reports coefficients obtained using a fixed-effects linear estimator. Time dummies are included in all models, but their coefficients are not reported for brevity. In Panel A, the dependent variable represents the probability of adult overweight (Columns 1-2) and adult obesity (Columns 3-4). In Panel B, it represents the probability of child overweight (Columns 1-2) and child obesity (Columns 3-4). Data from the 2004 to 2015 waves of the CHNS were used in estimation. T-statistics calculated using standard errors clustered at the individual level are in parentheses. The definitions of all variables are provided in Table C.1. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

Table 4.7: IV estimates for the probability of being overweight/obese

VARIABLES	**(1) First Stage**	**(2) Overweight**	**(3) Obese**
Internet_comm	0.050***		
	(9.30)		
Internet		0.0203***	0.0140***
		(4.87)	(4.35)
Age	-0.047***	0.0162***	0.0128**
	(-4.81)	(4.97)	(2.98)
Married	0.009	0.120	0.087**
	(0.20)	(0.84)	(2.70)
Nevermarried	-0.046	-0.228***	-0.134*
	(-0.98)	(-6.34)	(-2.06)
Divorced	0.031	-0.0766	0.650*
	(0.61)	(-0.46)	(2.35)
Widowed	-0.010	-0.133	0.510*
	(-0.23)	(-0.93)	(2.00)
Elementary	0.023***	0.717*	0.517*
	(3.97)	(1.97)	(2.28)
Middleschool	0.030***	0.728*	0.882*
	(3.97)	(2.02)	(2.23)
Highschool	0.078***	0.389	0.592
	(5.52)	(1.15)	(1.30)
College	0.168***	-0.370	-0.203
	(6.60)	(-1.12)	(-0.45)
Lnhhincome	0.001**	-0.0103	-0.0037*
	(2.15)	(-0.01)	(-1.98)
Employed	0.032***	-0.0301	-0.0532

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Table 4.7 – continued from previous page

VARIABLES	(1) First Stage	(2) Overweight	(3) Obese
	(6.24)	(-1.22)	(-1.64)
Insurance	-0.064***	0.0723*	0.0778
	(-11.38)	(2.42)	(1.95)
Health	0.013***	-0.108***	-0.0143
	(2.64)	(-3.59)	(-0.37)
HBP	-0.009	0.528***	0.550***
	(-1.29)	(16.25)	(14.39)
Diabetes	-0.010	0.398***	0.311***
	(-0.62)	(6.27)	(4.36)
Myocardial	-0.010	0.133	0.172
	(-0.60)	(1.19)	(1.36)
Apoplexy	0.003	-0.146	-0.0393
	(0.21)	(-1.57)	(-0.36)
Eversmoke	0.014*	-0.222***	-0.240***
	(1.71)	(-7.38)	(-5.96)
Phyact	0.044***	-0.204***	-0.285***
	(4.75)	(-3.39)	(-3.59)
Constant	2.153***	-2.576*	-1.728
	(4.85)	(-2.98)	(-0.96)
P-value Exogeneity		0.000***	0.000***
First Stage F-stat	47.32		
Observations	33,621	33,621	33,621
Number of id	14,009	14,009	14,009

Notes: This table reports coefficients obtained using the IV probit estimator. Time dummies are included in all models, but their coefficients are not reported for brevity. The p-value exogeneity test is the Wald test of exogeneity of the instruments. The F-statistics of the

*first stage regression of the Internet are also reported in Column (1). Data from the 2004 to 2015 waves of the CHNS were used in estimation. T-statistics calculated using standard errors clustered at the individual level are in parentheses. The definitions of all variables are provided in Table C.1. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

Table 4.8: Fixed-effects linear estimates for BMI

VARIABLES	BMI				
	(1) All	(2) Male	(3) Female	(4) Rural	(5) Urban
Panel A: Adults					
Internet	0.113***	0.142***	0.078	0.077	0.145***
	(3.24)	(2.92)	(1.56)	(1.38)	(3.28)
Control variables	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES
Observations	46,827	22,263	24,564	29,427	17,400
Number of id	19,930	9,488	10,434	11,710	8,212
Panel B: Children					
Internet	0.175***	0.181***	0.153	0.134	0.214***
	(5.98)	(4.20)	(1.30)	(1.45)	(4.11)
Control variables	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES
Observations	3,309	1,380	1,178	1,646	912
Number of id	2,394	1,002	893	1,199	696

*Notes: This table reports coefficients obtained using a fixed-effects linear estimator. Time dummies are included in all models, but their coefficients are not reported for brevity. The dependent variables represent BMI for adults in Panel A and children in Panel B. In each panel, the Columns represent the overall sample (Column 1), males (Column 2), females (Column 3), rural residents (Column 4), and urban residents (Column 5), respectively. Data from the 2004 to 2015 waves of the CHNS were used in estimation. T-statistics calculated using standard errors clustered at the individual level are in parentheses. The definitions of all variables are provided in Table C.1. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

Table 4.9: Fixed-effects linear probability estimates for the probability of suffering from central obesity

Central obesity	**(1) All**	**(2) Male**	**(3) Female**	**(4) Rural**	**(5) Urban**
Internet use	0.024*	0.001	0.047***	0.017	0.034
	(1.92)	(0.08)	(2.66)	(1.03)	(1.82)
Control variables	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES
Observations	26,317	12,594	13,723	16,577	9,740
Number of id	16,357	7,819	8,538	9,882	6,475

*Notes: This table reports coefficients obtained using a fixed-effects linear estimator. Time dummies are included in all models, but their coefficients are not reported for brevity. The dependent variables represent the probability of central obesity for the full sample (Column 1), males (Column 2), females (Column 3), rural residents (Column 4), and urban residents (Column 5), respectively. Data from the 2004 to 2015 waves of the CHNS were used in estimation. T-statistics calculated using standard errors clustered at the individual level are in parentheses. The definitions of all variables are provided in Table C.1. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

Table 4.10: Effect of Internet usage time on overweight and obesity

VARIABLES	**(1)** **Overweight**	**(2)** **Obesity**	**(3)** **Overweight618**	**(4)** **Obesity618**
Internet time	0.0001***	0.0001	0.0008***	0.000
	(2.95)	(0.27)	(2.72)	(0.25)
Control variables	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	31,956	31,956	2,784	2,784
Number of id	16,334	16,334	2,237	2,237

*Notes: This table reports coefficients obtained using a fixed-effects linear estimator. Time dummies are included in all models, but their coefficients are not reported for brevity. The dependent variable represents the probability of adult overweight (Column 1), adult obesity (Column 2), child overweight (Column 3), and child obesity (Column 4). Data from the 2004 to 2015 waves of the CHNS were used in estimation. T-statistics calculated using standard errors clustered at the individual level are in parentheses. The definitions of all variables are provided in Table C.1. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

Table 4.11: Fixed-effects linear probability estimates for the probability of being overweight/obese controlling dietary quality

VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**
	Overweight	**Obesity**	**Overweight618**	**Obesity618**
Internet use	0.012**	0.004	0.084***	0.129*
	(2.51)	(0.82)	(2.72)	(1.96)
Healthy diet	-0.019***	-0.008*	-0.011**	-0.040
	(-3.16)	(-2.16)	(-2.35)	(-0.45)
Other control variables	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	38,773	38,773	1,960	1,960
Number of id	17,730	17,730	1,919	1,919

*Notes: This table reports coefficients obtained using a fixed-effects linear estimator. Time dummies are included in all models, but their coefficients are not reported for brevity. The dependent variable represents the probability of adult overweight (Column 1), adult obesity (Column 2), child overweight (Column 3), and child obesity (Column 4). Data from the 2004 to 2015 waves of the CHNS were used in estimation. T-statistics calculated using standard errors clustered at the individual level are in parentheses. The definitions of all variables are provided in Table C.1. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

Table 4.12: Mechanisms test for physical inactivity, frequent drinking, and sleep deprivation

Panel A	**(1)**	**(2)**	**(3)**
	Physical Inactivity	**Frequent Drinking**	**Sleep Deprivation**
Internet Use	0.043***	0.055***	0.049**
	(6.505)	(8.044)	(2.435)
Control Variables	YES	YES	YES
Individual FE	YES	YES	YES
Time FE	YES	YES	YES
Observations	46,827	46,827	46,827
Number of id	19,922	19,922	19,922
Adj R^2	0.019	0.044	0.023
Panel B		**Overweight**	
Internet Use	0.015**	0.015**	0.014**
	(2.207)	(2.213)	(2.112)
Physical Inactivity	0.042**		
	(1.839)		
Frequent Drinking		0.008	
		(1.300)	
Sleep Deprivation			0.015***
			(3.529)
Control Variables	YES	YES	YES
Individual FE	YES	YES	YES
Time FE	YES	YES	YES
Observations	46,827	46,827	46,827
Number of id	19,922	19,922	19,922
Adj R^2	0.0227	0.0226	0.0228
Sobel Test Z	2.807***	6.649	1.976**

Notes: This table reports coefficients obtained using a fixed-effects linear estimator. Time dummies are included in all models, but their coefficients are not reported for brevity. Under

*the null hypothesis of no mediation effect, the Sobel tests are used to test whether a mediator carries the influence of a given independent variable to a dependent variable. Data from the 2004 to 2015 waves of the CHNS were used in estimation. T-statistics calculated using standard errors clustered at the individual level are in parentheses. The definitions of all variables are provided in Table C.1. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

Table 4.13: Mechanisms test of four nutrients intake

Panel A	**(1)**	**(2)**	**(3)**	**(4)**
	Energy	**Fat**	**Carbohydrate**	**Protein**
Internet Use	0.056***	0.067***	-0.132***	-0.001
	(11.33)	(7.64)	(-22.42)	(-0.22)
Control Variables	YES	YES	YES	YES
Individual&Time FE	YES	YES	YES	YES
Observations	38,773	38,773	38,773	38,773
Number of id	19,922	19,922	19,922	19,922
Adj R^2	0.081	0.050	0.124	0.080
Panel B			**Overweight**	
Internet Use	0.009***	0.010***	0.016***	0.021***
	(2.52)	(3.07)	(2.56)	(2.83)
Energy	0.032***			
	(5.42)			
Fat		0.025***		
		(5.81)		
Carbohydrate			-0.015**	
			(2.28)	
Protein				-0.070***
				(10.12)
Control Variables	YES	YES	YES	YES
Individual&Time FE	YES	YES	YES	YES
Observations	38,773	38,773	38,773	38,773
Number of id	17,730	17,730	17,730	17,730
Adj R^2	0.054	0.054	0.053	0.056
Sobel Test Z	4.88***	4.62***	-1.26	-0.218

Notes: This table reports coefficients obtained using a fixed-effects linear estimator. Time dummies are included in all models, but their coefficients are not reported for brevity. Under the null hypothesis of no mediation effect, the Sobel tests are used to test whether a mediator

*carries the influence of a given independent variable to a dependent variable. Data from the 2004 to 2015 waves of the CHNS were used in estimation. T-statistics calculated using standard errors clustered at the individual level are in parentheses. The definitions of all variables are provided in Table C.1. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

Chapter Five

Conclusion

Mental health and obesity have become increasingly significant public health issues in China. The primary objective of this thesis is to explore how micro and macro-level factors, such as changes in family structure, financial development, and the rise of ICT, affect them. Through a comprehensive analysis of large-scale datasets, including the CHARLS and the CHNS, this thesis presents three separate studies that provide new insights into the impacts of young leavers and financial development on mental health as well as the influence of Internet usage on overweight/obesity.

5.1 Summary of Main Findings

Chapter 2 investigates the impact of the younger generation departing the household on the mental health of the remaining household members. I find that the mental health of left-behind household members tends to improve once younger members leave the household upon gaining financial independence. Further, through mechanism analysis, I find that the reason for this positive effect is that the departure of younger members of the household reduces the economic and caregiving burden on the elderly. As young individuals leave, they

typically free up households' resources and often provide financial support to the left-behind family members in the form of remittances, which alleviates the financial constraints of the household. This enables left-behind household members to increase their consumption, thus offsetting the emotional losses that might arise from the absence of younger family members.

Chapter 3 explores the relationship between regional financial development and mental health. I find a significant positive relationship between financial development and the mental health of the residents, with a one standard deviation increase in the city-level financial development index being associated with a 1.9 percentage-point decrease in the probability of showing depressive symptoms. My results are robust when using a variety of different specifications, as well as different measures of financial development and estimation methods. The beneficial effects of financial development on mental health are higher for older respondents, respondents with poor physical health, respondents who live in rural areas, and respondents with low educational attainment, all of whom are likely to face significant financing constraints. I therefore conclude that financial development benefits people's mental health by reducing the financing constraints they face.

Chapter 4 investigates the link between Internet use and overweight/obesity in China, including both children and adults. The findings reveal a significant positive correlation between Internet usage and the likelihood of being overweight. About heterogeneity analysis, I identify a notable connection between internet usage and being overweight among men across various age groups but not among females. Additionally, among rural adults, internet usage is significantly associated with being overweight, whereas this link is absent in urban areas. Interestingly, for children, the pattern is reversed, with a stronger association found in urban areas compared to rural regions. Moreover, my mechanism analysis highlights several factors that help explain the effect of internet use on body weight. These factors include reduced sleep duration, decreased physical activity, and higher consumption of energy and fats.

5.2 Policy Implications

The findings of this thesis offer several important policy implications for improving public health outcomes in China, particularly in rural areas and among vulnerable populations such as the elderly and children. These implications can guide government initiatives aimed at mitigating the adverse effects of family structure changes, financial constraints, and digital behaviour on both mental and overweight/obesity.

Based on findings from Chapter 2, policies should focus on maximising the benefits of increased consumption and financial transfers for left-behind household members while, at the same time, mitigating the emotional challenges of family separation. The government could introduce initiatives to encourage regular financial support from young, independent individuals to their left-behind family members through tax incentives or other financial benefits for those who provide consistent transfers. Additionally, the government could strengthen financial security for elderly family members left behind by expanding pension schemes or offering social welfare programs that ensure they continue to benefit from increased household consumption. At the same time, enhancing access to affordable communication technologies, such as video calls and social media platforms, would help maintain emotional connections between family members despite physical separation, reducing the negative psychological impact. While promoting independent living, policies could also support young individuals who choose to live close to or with their families, offering financial assistance to balance their economic independence with the emotional well-being of the left-behind members. Moreover, expanding employment opportunities or community-based programs for left-behind family members, particularly older adults, could further offset the potential emotional and economic losses.

Chapter 3 discusses the important role of financial development in improving the mental health of Chinese residents, especially for those with financing constraints, such as

older adults and rural residents. To improve mental health, policymakers should focus on increasing access to financial services in underdeveloped areas and strengthening financial infrastructure in rural regions. The government can expand banking services in rural areas by collaborating with fintech companies or microfinance institutions. By making credit, savings accounts, and insurance products more accessible, residents can reduce financial stress, which positively impacts their mental health. Additionally, with the rapid development of Internet infrastructure, digital finance has greatly increased financial inclusion. Therefore, policies should encourage residents to improve their digital skills and promote the use of digital financial services. This helps vulnerable groups manage their financial needs better and lowers mental health risks. Lastly, targeted financial assistance programs, such as subsidised loans for healthcare or home repairs, can reduce the financial burden on older adults, improving their overall mental well-being.

Chapter 4 highlights the growing health risks associated with Internet use, in particular the strong link with overweight. In response to these findings, the government should take action by launching comprehensive public health campaigns aimed at promoting healthier lifestyles and mitigating the negative impacts of excessive Internet use. For instance, one important area might be the regulation of online advertising, including advertising for unhealthy foods, for which children are an important target audience. Stricter controls over such advertising, as well as monitoring content in Internet cafes and on social media platforms, could reduce exposure to unhealthy dietary influences. In addition to advertising regulations, the government should actively promote public participation in physical activity by investing in public facilities such as parks, sports centres and fitness programmes. Also, promoting the benefits of regular exercise at the national and local levels can help offset the long-term health risks of sedentary behaviour resulting from excessive Internet use. In addition, public health policies can combine nutrition education with digital literacy training to teach people about the importance of healthy eating and help them use the

internet more effectively and healthily. For parents and schools, children can be educated about the risks of excessive screen use while promoting a balanced diet and ensuring that young people develop healthier habits both online and offline.

5.3 Limitations and Future Research

Chapter 2 is limited by the short timeframe of the dataset (2011-2013). As a result, it does not account for the long-term consequences of family separations. The lack of more waves of data containing relevant variables restricts my understanding of whether the positive effects I identified on the mental health of left-behind household members after the departure of a younger member of the household persist or if their mental health deteriorates over time due to prolonged separation or other factors. Additionally, while I used panel data techniques and robustness checks, unobserved variables such as family dynamics and emotional ties, which could simultaneously influence both the decision to leave and mental health, remain potential confounders. Future research should explore datasets with more waves of relevant data and more nuanced aspects of family relationships to clarify the causal mechanisms behind these findings.

Chapter 3 also faces limitations. The underreporting of mental health issues due to cultural stigma could result in an underestimation of the true effects of financial development on mental health. Furthermore, while strong associations were identified, causality remains uncertain. Future research should leverage more sophisticated econometric techniques, such as instrumental variable approaches or natural experiments, to better isolate the causal impact of financial development on mental health. Additionally, as financial systems and technologies evolve, future studies should continue to assess how innovations in digital finance, especially in underbanked areas, influence mental health outcomes over time.

In Chapter 4, the fast-evolving nature of Internet use limits the relevance of my findings over time. Moreover, while I control for several confounding factors, unobserved variables like individual characteristics, social behaviours, and familial habits behind Internet use may still bias the results. Future research should examine these unobserved influences and adopt a dataset with more waves to capture the long-term health impacts of Internet use, particularly in children. As Internet penetration and digital behaviours continue to shift, further exploration of how these trends intersect with public health is crucial.

In conclusion, while my studies provide important insights and have clear policy implications, such as encouraging family communication, expanding financial access, and promoting healthier Internet habits, they also face methodological and contextual limitations. Future research should focus on addressing these gaps, exploring longer-term effects, refining causal relationships, and considering the rapidly changing social and technological landscapes to offer more comprehensive solutions to the problems I identified.

Appendix One

Appendix for Chapter 2

A.1 Control Variable Selection

$Z_{i,t}$ is the vector for control variables. There are four sets of control variables. First, we follow Lauber et al. (2003), Takagi et al. (2013) and Dour et al. (2014) to incorporate demographic characteristics as follows. Literature has found that depressive symptoms tend to increase with age (Woodall et al., 2010; Dour et al., 2014), potentially due to the gradual decline in physical health, increased social isolation, and losses associated with ageing, all of which significantly heighten the risk of mental health issues (Takagi et al., 2013). Thus, we anticipate a positive coefficient for the continuous variable representing the respondent's age. A Large body of literature [1] finds that women are generally more prone to depression than men. This might be due to factors such as hormonal differences, social roles, and other contributing elements. Marital status may significantly influence mental health, with married individuals showing lower rates of depressive symptoms. This may be due to greater access to coping resources and stronger social and emotional support (Kessler and Essex, 1982; Cutrona, 1996). Thus, we anticipate a negative correlation between the dummy variable for being married and the mental health indicators.

[1] See, eg., Kuehner (2017);Gigantesco et al. (2019) and Otten et al. (2021)

The second set of controls we consider is the economic and social status of individuals as follows. Individuals with lower incomes are more likely to experience financial stress, which can lead to increased anxiety and depression (Lorant et al., 2003). We therefore include the logarithm of income[2] to the control variables in our regressions and the expected coefficient to be negative. Lower education may be linked to insufficient resources for managing mental health and unstable work environments. Therefore, we include dummy variables for the respondent's highest education level[3] and expect a negative sign for the coefficient. Literature indicates that unemployment is tied to economic hardship and psychological distress. Stressful and insecure jobs with poor conditions can also heighten anxiety and depression (Tennant, 2001; Waddell, 2006). Thus, we expect unemployment to be associated with worse mental health conditions.

Next, the third set of control variables follows Daniel et al. (2004); Geoffroy et al. (2020); Du et al. (2022) to consider the influence of lifestyle habits. Magee and Clarke (2021) suggest smoking is negatively associated with depressive symptoms. Alcohol consumption also correlates with mental health, with some studies suggesting that moderate drinking is positively associated with both mental and physical health, while both excessive consumption and complete abstinence are linked to poorer health outcomes and deteriorating mental health (Bell and Britton, 2014; Castillo-Carniglia et al., 2019). Therefore, we hypothesise that smokers are at a higher risk of depression, while alcohol consumption might be associated with either an increased or decreased risk of depression. Previous research indicates a strong positive correlation between social participation and mental health, as it provides emotional

[2]In Section 2.4, we showed that the change of elderly consumption is a function of net transfer (τ in Equation (2.4)). For the empirical analysis in this section, we use the change of the net transfer, i.e. ΔNT. We claim that these two measurements essentially present the same insights. This is because, in the theoretical model, we assume the monetary transfer from the old-generation member to the young-generation member is 0 before the departure of descendants. However, this number could be non-zero in the empirical data. Therefore, we use the first-order difference in our empirical analyses.

[3]This is because, in the theoretical model, we assume the monetary transfer from the old-generation member to the young-generation member is 0 before the departure of descendants. However, this number could be non-zero in the empirical data. Therefore, we use the first-order difference in our empirical analyses.

support and a sense of belonging and promotes an active lifestyle, thereby enhancing overall mental well-being and reducing loneliness and anxiety (Chiao et al., 2011; Yue et al., 2022). Hence, we anticipate a significant negative association between social participation and the likelihood of experiencing depressive symptoms.

Finally, we control for respondents' physical health status. We consider measurements including self-rated health, chronic diseases, and self-care ability. Self-rated health is categorized as very good, fair, or bad health and is a crucial indicator of overall well-being (Wu et al., 2013). Chronic illnesses are strongly associated with higher depression rates, as they cause both physical discomfort and psychological stress (Katon, 2003). The loss of self-care abilities, whether in ADLs or IADLs, can lead to feelings of helplessness and increase the risk of depression (Bruce, 2001). Additionally, we account for the total number of limitations in ADLs and IADLs. We expect that individuals with chronic illnesses, poor self-care abilities, or bad self-rated health are more likely to suffer from depression.

A.2 Balancing Tests

Table A.3 shows the results of the balance test performed after PSM when the dependent variable is the CESD score, highlighting how well the treatment and control groups are matched. Column (3) indicates the difference between the treated and control groups for each covariate, with values close to zero suggesting that the matching was effective. Column (4) shows the significance of the difference between the means of the treated and control groups; non-significant values indicate no significant difference, further confirming balance. The results show that most covariates are well balanced, with low per cent bias and non-significant t-tests, indicating that the matching process was successful. Based on the results, we obtain that for all condition variables, the null hypothesis that there is no difference

in means between the matched treatment group and the matched control group cannot be rejected. This result also shows that the standardised percentage bias specific to the mean variable after matching is usually below the 5% threshold. Finally, our B-statistics and R-statistics meet Rubin (2001) suggested criteria for a balanced sample of less than 25 and between 0.5 and 2. These statistics indicate that the matching process precludes meaningful differences in matching dimensions observed between treatment and control group respondents.

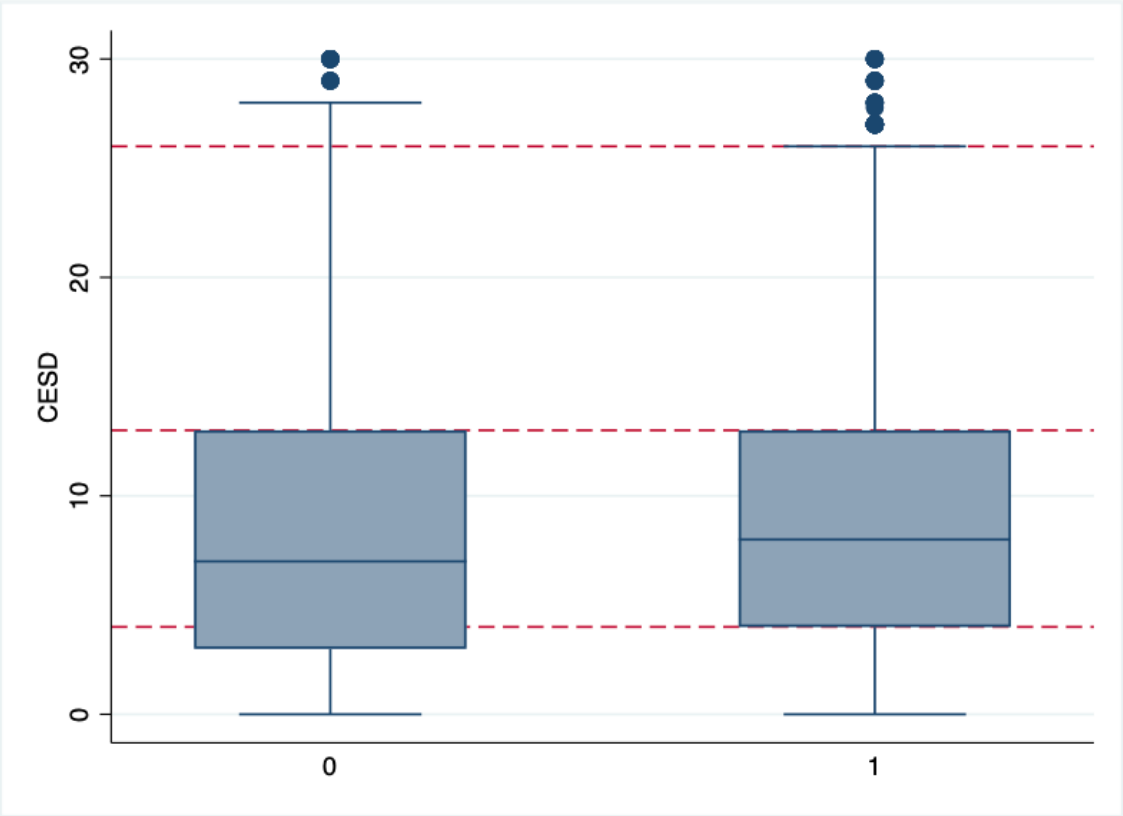
A.3 Selection Bias

The underlying endogeneity in our paper stems from selection bias. If a household member has poor mental health, the young-generation member may be less likely to move out, as they may need to spend more time caring for the older members. Conversely, in households where young members do move out, it is less likely that the older members have poor mental health. To statistically demonstrate this using our main dataset, we present a box plot for CESD scores in the treatment and control groups in Figure A.1. The left and right boxes represent the CESD distribution for the control and treatment groups, respectively. In this figure, we restrict our sample to 2011, which is the year before treatment took place in our sample. The red dashed lines, from bottom to top, indicate the higher 25th percentile, lower 75th percentile, and lower 99th percentile of CESD scores for the control and treatment groups. It is evident that for the control group (left box), the 99th percentile CESD score is higher than that of the treatment group (right box), indicating more severely depressed individuals in households without departing descendants. This suggests that the presence of departing descendants is associated with better mental health for the older-generation members, which may undermine the reliability of our empirical findings.

We demonstrate that our benchmark results are not driven by this confounding factor using several approaches. First, as seen in Figure A.1, although there are more observations with extremely high CESD scores in the control group compared to the treatment group, the relationship is reversed when looking at the mean level. We find that the average CESD score (represented by the middle line in the box) is actually higher for households with young leavers before the departure took place. The gap between the groups is approximately 0.295, with a t-statistic of around 2, suggesting that we cannot reject the null hypothesis that there is no significant difference in the average CESD score between the treatment and control groups before the treatment occurred. Therefore, the potential for selection bias is likely small in the mean value regressions.

However, we aim to mitigate the confounding effect of selection bias further. To achieve this, we construct a more balanced sample and re-estimate Equations (2.5) and (2.6). In practice, we remove observations with CESD scores higher than 26, which corresponds to the 99th percentile for the treated group, as indicated by the top red dashed line in Figure A.1. This subsample excludes potential confounding cases where there is no young leaver due to the extremely poor mental health of elderly family members. The estimated treatment effects for this subsample are shown in Columns (1) and (2) of Table A.4. We find that the results are consistent with our benchmark findings. The magnitude of the effect in the extensive margin is estimated to be -0.682, which is larger than the -0.58 observed in the baseline results. Additionally, we consider a subsample with CESD scores between 4 and 13, representing the range between the bottom and middle red dashed lines in Figure A.1. In this subsample, the treated and control groups are more balanced in terms of CESD scores. The estimated treatment effects for this subsample are displayed in Columns (3) and (4) of Table A.4. Once again, the treatment effect of young leavers remains significantly negative, with its magnitude larger than that in the baseline results. The signs associated with the control variables are similar to those reported in the baseline results.

Figure A.1: Box plot for CESD score



Note: The data is based on our main regression sample where respondents were aged 45 and above in both waves of the survey, and households participated in both waves of the survey.
Source: Authors' calculations based on the CHARLS.

Table A.1: Variable definitions

VARIABLES	Type	Units/Categories
Mental health		
CESD	Continuous	Likert score for the 10-item Centre for Epidemiological Studies-Depression, ranged from 0 to 30.
Depressed	Dummy Variable	Have a risk of depression (if CESD $\geq$ 12) [1]; have not (if CESD $<$ 12) [0]
Independent variables		
Has Departing Descendants or not	Dummy Variable	Have the younger generation who moved out during the period 2011 – 2013 [1]; other [0]
Number Departing Descendants	Continuous	Total number of members of the younger generation who moved out during the period 2011 – 2013.
Control variables		
Age	Continuous	Years
Gander	Dummy Variable	Male [1]; female [0]
Married	Dummy Variable	Married or cohabitate [1]; other [0]
Never married	Dummy Variable	Never Married [1]; other [0]

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Table A.1 – continued from previous page

VARIABLES	Type	Units/Categories
Widowed	Dummy Variable	Widowed [1]; other [0]
Divorced	Dummy Variable	Divorced or separated [1]; other [0]
Illiterate	Dummy Variable	No schooling [1]; other [0]
Elementary	Dummy Variable	Elementary school degree and below [1]; other [0]
Middle school	Dummy Variable	Middle school degree [1]; no middle school degree [0]
High school	Dummy Variable	High school degree [1]; no high school degree [0]
College	Dummy Variable	College or equivalent degree and above [1]; other [0]
Working	Dummy Variable	Working [1]; not working [0]
Income	Continuous	Logarithm of the respondent's household's real income deflated using the CPI, taking 2011 as the base year. (Yuan)

Continued on next page

Table A.1 – continued from previous page

VARIABLES	Type	Units/Categories
Social	Dummy Variable	Involved in any social activities [1]; not involved [0]
Smoke now	Dummy Variable	Smoking now [1]; not smoking now [0]
Drink now	Dummy Variable	Drinking now [1]; not drinking now [0]
Limitation	Continuous	Total number of limitations, including ADLs and IADLs
Chronics	Continuous	Number of having these fourteen chronic diseases: hypertension, diabetes, emotion, heart problems, cancer, stroke, lung, memory problems, arthritis, asthma, liver, kidney, stomach, cholesterol
Good health	Dummy Variable	The respondent is in good health [1]; other [0]
Fair health	Dummy Variable	The respondent is in fair health [1]; other [0]
Bad health (Ref.)	Dummy Variable	The respondent is in bad health [1]; other [0]

Table A.2: Baseline results show all control variables

VARIABLES	**(1)** **CESD**	**(2)** **Depression**	**(3)** **CESD**	**(4)** **Depression**
Young move	-0.580***	-0.042**		
	(0.205)	(0.017)		
Number of Young moves			-0.244***	-0.020***
			(0.088)	(0.007)
Age	-0.001	0.005	-0.004	0.005
	(0.110)	(0.008)	(0.110)	(0.008)
Gender	-0.361	-0.064	-0.372	-0.065
	(1.024)	(0.076)	(1.025)	(0.077)
Married	-3.449***	-0.190***	-3.475***	-0.192***
	(0.810)	(0.065)	(0.808)	(0.065)
Never married	-0.627	-0.216**	-0.647	-0.217**
	(1.923)	(0.097)	(1.920)	(0.097)
Widowed	-1.838**	-0.092	-1.841**	-0.092
	(0.854)	(0.067)	(0.852)	(0.067)
Elementary	-0.854	-0.056	-0.269	-0.008
	(1.515)	(0.127)	(0.505)	(0.043)
Middle school	-1.852	-0.138	-1.252*	-0.088
	(1.425)	(0.120)	(0.747)	(0.063)
High school	-0.072	-0.003	0.536	0.048
	(1.039)	(0.077)	(1.022)	(0.095)
Social	-0.265*	-0.017	-0.264*	-0.017
	(0.139)	(0.011)	(0.139)	(0.011)
Smoke now	-0.340	-0.025	-0.333	-0.024
	(0.260)	(0.021)	(0.260)	(0.021)
Drink now	0.317	0.025	0.316	0.025
	(0.195)	(0.017)	(0.195)	(0.017)
Chronic	2.842***	0.260***	2.843***	0.260***

Continued on next page

Table A.2 – continued from previous page

VARIABLES	(1) CESD	(2) Depression	(3) CESD	(4) Depression
	(0.470)	(0.078)	(0.463)	(0.078)
Limitation	0.734***	0.043***	0.733***	0.043***
	(0.056)	(0.005)	(0.056)	(0.005)
Working	-0.258	0.010	-0.258	0.011
	(0.195)	(0.016)	(0.195)	(0.016)
Income	-0.033	-0.001	-0.032	-0.001
	(0.022)	(0.002)	(0.022)	(0.002)
Good health	-1.937***	-0.108***	-1.942***	-0.108***
	(0.267)	(0.022)	(0.267)	(0.022)
Fair health	-0.825***	-0.033**	-0.832***	-0.033**
	(0.203)	(0.016)	(0.203)	(0.016)
Observations	12,165	12,165	12,165	12,165
R-squared	0.079	0.047	0.079	0.048
Number of id	6,514	6,514	6,514	6,514

*Notes: The table reports the estimates of the baseline model. All models were estimated using a fixed-effects linear estimator. The dependent variable in Columns (1,3) is the CESD score, and in Columns (2,4), it is the probability of having depression. Data from the 2011 and 2013 waves of the CHARLS were used in estimation. Standard errors clustered at the household level are in parentheses. Time dummies and the interactions between provincial and time dummies are included in all models, but their coefficients are not reported for brevity. The definitions of all variables are provided in Table A.1. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

Table A.3: Balancing Tests

VARIABLES	**(1)** **Treated Mean**	**(2)** **Control Mean**	**(3)** **% Bias**	**(4)** **t-test (p-value)**
Age	57.716	57.756	-2.4	0.963
Gender	0.328	0.335	-3.4	0.673
Married	0.788	0.756	5.3	0.546
Never Married	0.0123	0.0111	3.2	0.879
Elementary	0.408	0.408	0	0.856
Widowed	0.189	0.188	0.8	0.908
Middle School	0.162	0.234	-5.1	0.737
Highschool	0.084	0.092	-2.8	0.753
Social	0.532	0.508	4.8	0.592
Smoke_now	0.616	0.632	-3.3	0.713
Drink_now	0.340	0.352	-2.5	0.778
Chronics	1.340	1.328	0.9	0.925
Limitation	0.666	0.668	-0.6	0.867
Working	0.748	0.756	-1.8	0.836
Income	6.2718	6.7742	-5.6	0.087
Good Health	0.253	0.251	0.8	0.897
Fair Health	0.686	0.686	0	1.000
B-statistic	21.6			
R-statistic	0.97			

Note: This table reports the balancing tests, with the treatment group being those with younger generation leavers. Columns (1) and (2) report the group means for the treatment group and the matched control group, respectively. The percentage deviation in column (3) is the

percentage difference in the means of the groups between the treatment and control groups relative to the square root of the average variance of the two groups. Column (4) reports the t-test to determine whether the group means of the relevant variables are statistically different between the treatment group and the control group. The statistic B is less than 25, and the statistic R between 0.5 and 2 indicate that the panel is sufficiently balanced (Rubin, 2001).

Table A.4: Specification check

VARIABLES	**(1)** **CESD**	**(2)** **CESD**	**(3)** **CESD**	**(4)** **CESD**
Young move	-0.682***		-0.628***	
	(0.200)		(0.192)	
Number of Young moves		-0.294***		-0.243***
		(0.087)		(0.084)
Control variables	Yes	Yes	Yes	Yes
Observations	12,012	12,012	5,577	5,577
Number of id	6,491	6,491	4,198	4,198

*Notes: The table reports the estimates of our baseline model using a more balanced sample. All models are estimated using a fixed-effects linear estimator. The dependent variable in all Columns is the CESD score. Data from the 2011 and 2013 waves of the CHARLS were used in estimation. Standard errors clustered at the household level are in parentheses. Time dummies and the interactions between provincial and time dummies are included in all models, but their coefficients are not reported for brevity. The definitions of all variables are provided in Table A.1. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

Appendix Two

Appendix for Chapter 3

B.1 The Peking University Digital Financial Inclusion Index of China

Since 2016, the research team of Peking University Digital Finance Research Centre and Ant Group Research Institute[1] has used Ant Group's massive data on digital finance to compile the PKU_DFIIC. The group constructs the DFI based on the following three dimensions: the breadth of digital financial coverage, the depth of digital financial use, and the degree of digitalization of financial inclusion. At present, the DFI contains 33 specific indicators in these three dimensions. Based on the above index system and the Hierarchical Analysis Method, a common index compilation method used in similar literature, the group compiled the Index for 31 provinces, 337 cities above prefecture level, and about 2,800 counties. In addition to the aggregate Index, the breadth of digital finance coverage Index, depth of digital finance usage index, and degree of financial digitisation index are also provided, as well as categorical indices for payments, insurance, monetary funds, credit services, investments,

[1]Alipay, owned by Ant Financial, is one of the largest mobile payment platforms in China. Alipay not only greatly facilitates residents' daily payments, transfers and financial management but also promotes the popularization of financial services, especially in more remote and underserved areas. In addition, Alipay has further expanded financing channels for individuals and small and micro enterprises through its innovative financial products such as Yu'e Bao and Huabei.

and credits under the depth of digital finance usage Index. The reliability of the DIF Index stems from its comprehensive methodology, which involves collecting a wide range of data from various credible sources, including financial statements, user surveys, and industry reports. This data is validated annually through methodological checks to ensure that the Index remains a strong indicator of the evolution of digital finance.

B.2 Original Questions in the CHARLS

B.2.1 CESD-10

The following are the original questions from CHARLS used to obtain the CESD-10 score with text in Chinese. The responses to the CES-D questions are rated on a 1-4. Likert scale from "Rarely or none of the time" to "Most or all of the time". We adopt Radloff (1977)'s suggestion to adjust the scoring of answers to a range of 0 to 3. For the eight negative questions, these answers are 0 = 'Rarely or none of the time', 1 = 'Some or a little of the time', 2 = 'Occasionally or a moderate amount of the time', and 3 = 'Most or all of the time'. For the two positive questions, DC13 and DC16, the reverse is true, with 0 = 'Most or all of the time' and 3 = 'Rarely or none of the time'.

The 10 items below refer to how you have felt and behaved during the last week. Choose the appropriate response
下面 10 道问题是有关您上周的感觉及行为，每道题目的答案都是一样的，包括很少或者根本没有，不太多，有时或者说有一半的时间还是大多数的时间，请您选择合适的答案

1. Rarely or none of the time (< 1 day) 很少或者根本没有（< 1 天）
2. Some or a little of the time (1-2 days) 不太多（1-2 天）

3. Occasionally or a moderate amount of the time (3-4 days) 有时或者说有一半的时间（3-4 天）

4. Most or all of the time (5-7 days) 大多数的时间（5-7 天）

DC009. I was bothered by things that don't usually bother me. 我因一些小事而烦恼。

DC010. I had trouble keeping my mind on what I was doing. 我在做事时很难集中精力。

DC011. I felt depressed. 我感到情绪低落。

DC012. I felt everything I did was an effort. 我觉得做任何事都很费劲。

DC013. I felt hopeful about the future. 我对未来充满希望。

DC014. I felt fearful. 我感到害怕。

DC015. My sleep was restless. 我的睡眠不好。

DC016. I was happy. 我很愉快。

DC017. I felt lonely. 我感到孤独。

DC018. I could not get going. 我觉得我无法继续我的生活。

B.2.2 Life Satisfaction

Furthermore, the original answers for life satisfaction are on a 1-5 scale, from "Completely satisfied" to "Not at all satisfied." To comply with the convention, we reverse the order of the answers to the questions, where 1 = 'Not at all satisfied' and 5 = 'Completely satisfied'.

DC028 Please think about your life-as-a-whole. How satisfied are you with it? Are you completely satisfied, very satisfied, somewhat satisfied, not very satisfied, or not at all satisfied?
总体来看，您对自己的生活是否感到满意？是极其满意，非常满意，比较满意，不太满意还是一点也不满意？

1. Completely satisfied 极其满意
2. Very satisfied 非常满意
3. Somewhat satisfied 比较满意
4. Not very satisfied 不太满意
5. Not at all satisfied 一点也不满意

Table B.1: Variable definitions

VARIABLES	Type	Units/Categories
Panel A:		
Mental Health		
CESD	Continuous	Likert score for the 10-item Centre for Epidemiological Studies-Depression, ranging from 0 to 30.
Depression	Dummy Variable	Has a risk of depression: Yes (CESD $\geq$ 12) [1]; Not (CESD $<$ 12) [0]
Severe Depression	Dummy Variable	Has a severe risk of depression: Yes (CESD $\geq$ 20) [1]; No (if CESD $<$ 20) [0]
Life Satisfaction	Continuous	5-point Likert scale items coded from 1 (very poor/not at all satisfactory) to 5 (very good/fully satisfactory).
Panel B:		
Control Variables		
Age	Continuous	Years
Gender	Dummy Variable	Male [1]; female [0]
Hukoudum	Dummy Variable	Non-agricultural hukou or unified hukou [1]; other [0]
Married	Dummy Variable	Married or cohabitating [1]; other [0]
Never Married	Dummy Variable	Never Married [1]; other [0]

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Table B.1 – continued from previous page

VARIABLES	Type	Units/Categories
Widowed	Dummy Variable	Widowed [1]; other [0]
Divorced	Dummy Variable	Divorced or separated [1]; other [0]
Illiterate	Dummy Variable	No schooling [1]; other [0]
Elementary	Dummy Variable	Elementary school degree and below [1]; other [0]
Middle School	Dummy Variable	Middle school degree [1]; no middle school degree [0]
High School	Dummy Variable	High school degree [1]; no high school degree [0]
College	Dummy Variable	College or equivalent degree and above [1]; other [0]
Working	Dummy Variable	Working [1]; not working [0]
Hyhhsize	Dummy Variable	Households with more than two members [1]; households with less than two members [0]
Lghhitot	Continuous	Logarithm of the respondent's household's real income deflated using the CPI, taking 2011 as the base year (Yuan)
Social	Dummy Variable	Is involved in any social activities [1]; not involved [0]
Smoke	Dummy Variable	Smoking now [1]; not smoking now [0]
Drink	Dummy Variable	Drinking now [1]; not drinking now [0]
Hoursleep	Continuous	Average daily actual sleeping hours (h)

Continued on next page

Table B.1 – continued from previous page

VARIABLES	Type	Units/Categories
Insurance	Dummy Variable	Has health insurance: Yes [1]; No [0]
Limitation	Continuous	Total number of limitations including ADLs and IADLs
Chronics	Continuous	Number of chronic diseases the respondent is suffering from: hypertension, diabetes, emotion, heart problem, cancer, stroke, lung, memory problem, arthritis, asthma, liver, kidney, stomach, cholesterol
Panel C:		
Financial Development		
N_bank_csmar	Continuous	Number of bank branches per year per city
N_bank_csmar_pc	Continuous	Number of bank branches per 1,000 population per year per city
FinDev1	Continuous	Ratio of total bank and non-bank loans in the city's financial system to the city's GRP
FinDev2	Continuous	Ratio of total deposits in the city's financial system to the city's GRP.
DFinDev	Continuous	Aggregate digital finance index divided by 100, obtained from PKU-DFIIC.
Panel D:		
Financing Constraints		

Continued on next page

Table B.1 – continued from previous page

VARIABLES	Type	Units/Categories
Elder	Dummy Variable	1 if the respondent is 65 years of age or older, and 0 otherwise.
Rural	Dummy Variable	1 if the respondent resides in a rural area, and 0 otherwise.
Lowedu	Dummy Variable	1 if the respondent has less than a middle school education, and 0 otherwise.
Lowconsum	Dummy Variable	1 if the respondent's consumption level is in the lowest quartile of the population, and 0 otherwise.
Bad_health	Dummy Variable	1 if the respondent self-reports their health as poor, and 0 otherwise.
ADL	Dummy Variable	1 if the respondent has limitations in Activities of Daily Living (e.g., bathing, dressing, eating), and 0 otherwise.
IADL	Dummy Variable	1 if the respondent has limitations in Instrumental Activities of Daily Living (e.g., preparing meals, managing finances), and 0 otherwise.
Severchronicdum	Dummy Variable	1 if the respondent suffers from at least one middle-grade or severe chronic disease (e.g., diabetes, cardiovascular disease, cancer), and 0 otherwise.

Table B.2: Effects of different measures of financial development on CESD score

VARIABLES	**(1)** **CESD**	**(2)** **CESD**	**(3)** **CESD**	**(4)** **CESD**
n_bank_csmar	-0.272***			
	(-3.08)			
n_bank_csmar_pc		-0.796**		
		(-2.21)		
FinDev2			-0.386***	
			(-2.40)	
DFinDev				-0.967**
				(-2.12)
Control Variables	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	55,328	55,328	55,328	55,328
Number of id	20,725	20,725	20,725	20,725

Notes: The table reports the estimates of Equation (3.1) *using different measures of financial development. All models were estimated using a fixed-effects linear estimator. The dependent variable in all models is the CESD score, which is a continuous variable with values ranging from 0 to 30. Data from the 2011 to 2018 waves of the CHARLS were used in estimation. T-statistics calculated using standard errors clustered at the individual level are in parentheses. Time dummies are included in all models, but their coefficients are not reported for brevity. The definitions of all variables are provided in Table B.1. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

Table B.3: Effects of different measures of financial development on the probability of having severe depression

VARIABLES	(1) Severe Depression	(2) Severe Depression	(3) Severe Depression	(4) Severe Depression
n_bank_csmar	-0.000			
	(-0.95)			
n_bank_csmar_pc		-0.004		
		(-0.04)		
FinDev2			-0.017**	
			(-2.36)	
DFinDev				-0.049**
				(-2.29)
Control Variables	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	55,328	55,328	55,328	55,328
Number of id	20,725	20,725	20,725	20,725

Notes: The table reports the estimates of Equation (3.1) *using different measures of financial development. All models were estimated using a fixed-effects linear estimator. The dependent variable in all models is the probability of having severe depression. Data from the 2011 to 2018 waves of the CHARLS were used in estimation. T-statistics calculated using standard errors clustered at the individual level are in parentheses. Time dummies are included in all models, but their coefficients are not reported for brevity. The definitions of all variables are provided in Table B.1. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

Table B.4: Effects of different measures of financial development on life satisfaction

VARIABLES	(1) Life Satisfaction	(2) Life Satisfaction	(3) Life Satisfaction	(4) Life Satisfaction
n_bank_csmar	0.027**			
	(2.08)			
n_bank_csmar_pc		0.154***		
		(2.60)		
FinDev2			0.009	
			(0.03)	
DFinDev				-0.050
				(-0.78)
Control Variables	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	55,328	55,328	55,328	55,328
Number of id	20,725	20,725	20,725	20,725

Notes: The table reports the estimates of Equation (3.1) *using different measures of financial development. All models were estimated using a fixed-effects linear estimator. The dependent variable in all models is the five-category variable of life satisfaction. Data from the 2011 to 2018 waves of the CHARLS were used in estimation. T-statistics calculated using standard errors clustered at the individual level are in parentheses. Time dummies are included in all models, but their coefficients are not reported for brevity. The definitions of all variables are provided in Table B.1. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

Table B.5: Impact of Different Financial Development Indicators on Depression Using a Correlated Random Effects Probit Model

VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**
	Depression	**Depression**	**Depression**	**Depression**
n_bank_csmar	-0.000**			
	(-2.77)			
n_bank_csmar_pc		-0.072**		
		(-2.28)		
FinDev2			-0.026***	
			(-3.76)	
DFinDev				-0.067**
				(-1.70)
Control Variables	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	55,328	55,328	55,328	55,328
Number of id	20,725	20,725	20,725	20,725

Notes: The table reports the estimates of Equation (3.1) *using different measures of financial development. All models were estimated using a correlated random effects probit model, and marginal effects were reported. The dependent variable in all models is the probability of having depression. Data from the 2011 to 2018 waves of the CHARLS were used in estimation. T-statistics calculated using standard errors clustered at the individual level are in parentheses. Time dummies are included in all models, but their marginal effects are not reported for brevity. The definitions of all variables are provided in Table B.1. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

Table B.6: Impact of different financial development indicators on severe depression using a correlated random effects probit model

VARIABLES	(1) Severe Depression	(2) Severe Depression	(3) Severe Depression	(4) Severe Depression
n_bank_csmar	-0.000			
	(-0.37)			
n_bank_csmar_pc		-0.002		
		(-0.18)		
FinDev2			-0.008***	
			(-3.20)	
DFinDev				-0.021**
				(-2.17)
Control Variables	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	55,328	55,328	55,328	55,328
Number of id	20,725	20,725	20,725	20,725

Notes: The table reports the estimates of Equation (3.1) *using different measures of financial development. All models were estimated using a correlated random effects probit model, and marginal effects were reported. The dependent variable in all models is the probability of having severe depression. Data from the 2011 to 2018 waves of the CHARLS were used in estimation. T-statistics calculated using standard errors clustered at the individual level are in parentheses. Time dummies are included in all models, but their marginal effects are not reported for brevity. The definitions of all variables are provided in Table B.1. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

Appendix Three

Appendix for Chapter 4

C.1 Details about the Selection of Control Variables

Firstly, this study incorporates gender, marital status, and age as key individual characteristics that are known to influence the prevalence of overweight and obesity in China. These factors are selected based on their demonstrated relationship with the obesity epidemic, as documented in the literature. Specifically, gender is included because research consistently shows differences in obesity rates between males and females, with males generally exhibiting higher rates of overweight and obesity (Flegal et al., 1998; Gallus et al., 2015). Therefore, the expected sign for the gender variable is positive. Marital status is also crucial, as previous studies have found that being married is often associated with higher body weight, likely due to changes in lifestyle and dietary habits after marriage (Sobal et al., 1992). Thus, we expect positive signs for the married variables, with being married particularly associated with a higher likelihood of being overweight or obese. Age is included as a continuous variable, given that obesity risk tends to increase with age due to metabolic changes and decreased physical activity, leading us to expect a positive correlation (Chapman, 2008; Swinburn et al., 2011).

Secondly, we control for personal lifestyle factors such as smoking status, exercise habits, and health insurance coverage, all of which have been shown to impact overweight

and obesity rates. Regular physical activity is expected to have a negative association with overweight and obesity, as it contributes to energy expenditure. Hence, the expected sign for the exercise variable is negative. Smoking status is included because smoking can influence metabolism and appetite, although the direction of its effect on body weight is mixed in the literature; however, it is generally expected to be negative due to the appetite-suppressing effects of nicotine (Dare et al., 2015; Courtemanche et al., 2018). Health insurance is included as it may increase access to healthcare and preventive services, potentially leading to better weight management, though it could also lead to a sense of security that might reduce motivation for healthy behaviour, making the expected sign uncertain (Kelly and Markowitz, 2009). These variables are critical in capturing lifestyle differences that may otherwise confound the relationship between Internet use and obesity.

Thirdly, this paper includes education, income, and employment status as socioeconomic determinants, acknowledging their significant impact on overweight and obesity. Education is expected to have a negative correlation with overweight and obesity, as higher education levels are often associated with greater health awareness and better dietary and exercise habits. Therefore, we anticipate negative signs for the education variables. Income is included as a continuous variable, with the expectation that higher income may correlate with both increased access to healthier food options and possibly greater consumption of calorie-dense foods, leading to a mixed or context-dependent expected sign. Employment status is included to capture the effects of occupational activity levels and income stability on body weight, with the expected sign likely being positive for employed individuals due to potential sedentary work environments. The socioeconomic factors for all variables are defined in detail in Table C.1 (Dinsa et al., 2012; Morris, 2007; Zhang et al., 2017).

C.2 Descriptive Statistics of Control Variables

Table 4.1 also shows descriptive statistics for control variables in this study. In our sample, the average age of participants is 44.27 years, with a nearly equal gender distribution (48.5% female). Most participants are married (84.4%), while 7.57% have never been married, 1.29% are divorced, and 6.37% are widowed. These marital status figures are consistent with those reported in other studies of similar age groups. 20.2% have only completed elementary education, 32.8% have a middle school education, and 20.3% have completed high school. Only 8.12% hold a college degree.

Additionally, parental education levels are higher for fathers (66.7%) than for mothers (50.7%), highlighting traditional gender disparities in educational opportunities. Household income shows considerable variation, with a mean of 13,433 units and a standard deviation of 12,855 units, indicating significant income inequality within the sample. Focus on health status, 14.4% report chronic illnesses, and 11.7% have high blood pressure. Additionally, 14.8% engage in regular physical activity, and 73.8% have health insurance coverage. Regarding lifestyle behaviours, 28.8% of participants have smoked at some point, and 30.7% have consumed alcohol.

Table C.1: Variable definitions

VARIABLES	**Type**	**Units/Categories**
Weight		
BMI	Continuous	Body Mass Index value
WHtR	Continuous	Ratio of waist circumference to height
Obese	Dummy Variable	Obese (if BMI $\geq$ 28 & age $\geq$ 18) [1]; other (if BMI $<$ 28 & age $\geq$ 18) [0]
Obese518	Dummy Variable	Obese (if age $\geq$ 5 & age $<$ 18) [1]; other (if age $\geq$ 5 & age $<$ 18) [0]
Central obese	Dummy Variable	Central obesity (if WHtR $>$ 0.5) [1]; other (if WHtR $\leq$ 0.5) [0]
Overweight	Dummy Variable	Overweight (if BMI $\geq$ 24 & age $\geq$ 18) [1]; other (if BMI $<$ 24 & age $\geq$ 18) [0]
Overweight518	Dummy Variable	Overweight (if age $\geq$ 5 & age $<$ 18) [1]; other (if age $\geq$ 5 & age $<$ 18) [0]
Control variables		
Age	Continuous	Respondent's age
Gender	Dummy Variable	Male [1]; female [0]
Married	Dummy Variable	Married [1]; otherwise [0]
Widowed	Dummy Variable	Widowed [1]; other [0]
Divorced	Dummy Variable	Divorced or separated [1]; otherwise [0]
Never married	Dummy Variable	Never married [1]; otherwise [0]

Continued on next page

Table C.1 – continued from previous page

VARIABLES	Type	Units/Categories
Employed	Dummy Variable	Working [1]; otherwise [0]
Ever smoke	Dummy Variable	Ever smoked [1]; otherwise [0]
Physical exercise	Dummy Variable	Have regular physical exercise [1]; otherwise [0]
lnincome	Continuous	Logarithm of real household income per capita in Yuan inflated to 2015.
Health condition	Dummy Variable	Was sick or injured during the past 4 weeks [1]; otherwise [0]
Insurance	Dummy Variable	Has health insurance [1]; otherwise [0]
HBP	Dummy Variable	Has high blood pressure [1]; otherwise [0]
Diabetes	Dummy Variable	Has diabetes [1]; otherwise [0]
Myocardial	Dummy Variable	Has myocardial disease [1]; otherwise [0]
Apoplexy	Dummy Variable	Has apoplexy [1]; otherwise [0]
Chronic	Dummy Variable	Has any one of the four chronic diseases: hypertension, diabetes, myocardial, and apoplexy. [1]; otherwise [0]
Illiterate (ref.)	Dummy Variable	Have not received education
Elementary	Dummy Variable	Elementary school degree [1]; otherwise [0]
Middle school	Dummy Variable	Middle school degree [1]; otherwise [0]

Continued on next page

Table C.1 – continued from previous page

VARIABLES	Type	Units/Categories
High school	Dummy Variable	High school degree [1]; otherwise [0]
College	Dummy Variable	College or equivalent degree and above [1]; otherwise [0]
Healthy diet	Dummy Variable	Daily diet meets the recommended standards for intake of four nutrients [1]; otherwise [0]
Internet usage		
Internet	Dummy Variable	Ever used the internet [1]; otherwise [0]
Internet time	Continuous	Daily Internet usage time for online chatting, web browsing, gaming, etc. (in minutes)
Mechanisms		
Physical inactivity	Dummy Variable	Not meets criteria for adequate physical activity [1]; otherwise [0]
Poor sleep	Dummy Variable	Less than 7 hours of sleep per night on a regular basis [1]; otherwise [0]
Frequent Drinking	Dummy Variable	Frequency of alcohol consumption per month
Energy	Continuous	3-Day average energy (kcal)
Fat	Continuous	3-Day average fat (g)
Carbohydrate	Continuous	3-Day average carbohydrate (g)
Protein	Continuous	3-Day average protein (g)

Table C.2: BMI thresholds for overweight and obesity by age and gender in China

Age	**Male**		**Female**	
	Overweight	**Obesity**	**Overweight**	**Obesity**
6∼7	17.4-19.1	≥19.2	17.2-18.8	≥18.9
7∼8	17.8-19.7	≥19.8	17.6-19.5	≥19.6
8∼9	18.4-20.5	≥20.6	18.4-20.3	≥20.4
9∼10	19.1-21.2	≥21.3	19.1-21.1	≥21.2
10∼11	19.8-22.1	≥22.2	23.4-22.0	≥22.1
11∼12	20.3-23.5	≥23.6	19.8-23.2	≥23.3
12∼13	21.0-24.6	≥24.7	20.6-24.4	≥24.5
13∼14	21.9-25.6	≥25.7	22.6-25.0	≥25.1
14∼15	22.6-26.3	≥26.4	23.0-25.7	≥25.8
15∼16	23.1-26.8	≥26.9	23.4-26.2	≥26.3
16∼17	23.5-27.3	≥27.4	23.7-26.7	≥26.8
17∼18	23.8-27.7	≥27.8	23.4-27.1	≥27.2
18+	24-27.9	≥28	24-27.9	≥28

Note: Sources from China Health Commission 2018.

Table C.3: Dietary reference intakes (DRIs) for Chinese residents

Age (years)	**Energy (kcal/day)**		**Fat (g/day)**		**Carbohydrate (g/day)**		**Protein (g/day)**	
	Male	**Female**	**Male**	**Female**	**Male**	**Female**	**Male**	**Female**
7-10	1700-2100	1700-2100	47.2-81.7	47.2-81.7	212.5-341.2	212.5-341.2	40-50	40-50
11-14	2200-2500	2000-2200	61.1-97.2	55.6-85.6	275.0-406.2	250.0-357.5	45-55	45-55
15-17	2500-2800	2200-2400	69.4-108.9	61.1-93.3	312.5-455.0	275.0-390.0	65-75	60-70
18+	2250-2600	1800-2200	50.0-86.7	40.0-73.3	281.2-422.5	225.0-357.5	65-85	55-70

Note: Sources from Chinese Nutrition Society in 2016.

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