

Health Insurance, Sleep, and Healthcare Utilization: Evidence from China

by

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A thesis submitted to the University of Birmingham for the degree of

DOCTOR OF PHILOSOPHY

Department of Economics

Birmingham Business School

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University of Birmingham

September 2024

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Abstract

China's health insurance system has witnessed significant changes over the past few decades. In 1998, the Urban Employee Basic Medical Insurance (UEBMI) was established. In 2002, the Urban Resident Basic Medical Insurance (URBMI) started, followed by the New Rural Cooperative Medical Insurance (NRCMI) in 2007. Subsequently, some provinces launched pilot programs to merge URBMI and NRCMI into the Urban and Rural Resident Medical Insurance (URRMI), and by 2021, this unification was largely completed across all provinces. How do these changes affect middle-aged and older adults and children in this policy context?

Firstly, this study examines the effects of three public health insurance (NRCMI, URBMI, and UEBMI) and private health insurance on the mental health of middle-aged and older adults. It also explores how transitions between these public insurances impact mental health. Additionally, it investigates the influence of the URRMI pilot policy on mental health.

Secondly, this research explores how health insurance affects children's healthcare utilization. It compares children with public health insurance to those with private insurance in terms of healthcare utilization. Furthermore, it investigates how the URRMI merger policy impacts healthcare use among children. This research also explores how insurance status affects income-related inequalities in children's healthcare utilization.

Finally, this study investigates how sleep duration and sleep quality relate to out-of-pocket (OOP) medical expenditure and the likelihood of catastrophic health expenditure (CHE) for middle-aged and older adults.

Acknowledgments

When I read others' acknowledgments, I was often moved by their many heartfelt expressions of gratitude. Now, I truly understand and feel this genuine appreciation that naturally arises in moments like these.

First and foremost, I would like to thank my lead supervisor, Professor Alessandra Guariglia. She has been a guiding light on my academic journey, always encouraging and supporting me while carefully pointing out my mistakes. Her guidance in independent research and her careful review of every document I submitted have been invaluable. Without her help, overcoming the challenges in my research would have been very difficult.

Secondly, I am grateful to my co-supervisor, Professor Nicholas Horsewood. During my graduate studies, he taught me econometrics, and I fondly remember his humorous lectures that made classes both enjoyable and enriching. In my doctoral studies, he has consistently provided insightful suggestions and assistance for each chapter of my thesis.

I also sincerely thank Professor Sasha Talavera and Dr. Yi Liu. I greatly appreciate the interesting and practical advice they offered after my presentations. Additionally, I am thankful to everyone who gave me suggestions following my participation in conferences such as the EUHEA Conference 2024, the 2nd International Workshop on the Chinese Development Model, the 2023 Birmingham Business School Conference, and other workshops and seminars.

I am deeply grateful to my friends, Yibei Qu, Haokun Pang, Ye Cheng, Yujing Yang, Duiyi Dai, Yangjun Han, and many others. We spent countless hours together, studying, discussing ideas, and writing papers. Your encouragement and shared laughter made this journey much more enjoyable.

I would like to express my heartfelt gratitude to my junior and senior colleagues, Naijie Guan, Fangzhou Xu, Yiming Yang, Dongqiang Liang, Lin Tian, Lin Fu, and many others, whose generous sharing of their experiences have truly benefited me. Their kindness and guidance have greatly enriched my journey and made it more meaningful.

I want to extend my heartfelt thanks to my fiancé, my best friend, who began the PhD journey alongside me. Your hard work has always inspired me to keep moving forward. Thank you for embracing all my emotions with patience and understanding. I am truly grateful for your determined support and companionship.

Lastly, I wish to thank my family. Thank you to my mother for always encouraging me since childhood and helping me believe in my ability to overcome many difficulties. I also thank my father for his endless love and support. Special thanks to my cheerful grandmother, whose video calls always bring me joy and energy.

Thank you all for your continued support and encouragement throughout this journey.

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List of Abbreviations

UEBMI	Urban Employee Basic Medical Insurance
URBMI	Urban Resident Basic Medical Insurance
NRCMI	New Rural Cooperative Medical Insurance
URRMI	Urban and Rural Resident Medical Insurance
OOP	Out-of-Pocket
CHE	Catastrophic Health Expenditure
LIS	Labor Insurance Scheme
SOEs	State-Owned Enterprises
GIS	Government Insurance Scheme
CMS	Cooperative Medical System
CFPS	China Family Panel Survey
CHARLS	China Health and Retirement Longitudinal Study
DID	Difference-in-Differences
IADLs/ADLs	Instrumental Activities of Daily Living / Activities of Daily Living
CRE	Correlated Random Effect
FE	Fixed Effects

Chapter 1 Introduction

1.1 Healthcare background and motivations

In 1951, under the Labor Insurance Scheme (LIS), urban employees working in state-owned enterprises (SOEs) ¹ in China received nearly free healthcare. The following year, the government implemented the Government Insurance Scheme (GIS), offering free medical treatment to civil servants, government officials, and public sector workers. In addition, rural residents relied on the Cooperative Medical System (CMS), which started in 1955. It mainly covered members of agricultural collectives, who paid a small fee², in return, received basic medical services. According to Shi and Liu (2018), due to the collapse of the rural cooperative system ³ at the end of the 1980s, CMS almost entirely collapsed.

By the 1990s, economic reforms led to the closing down of many SOEs, resulting in many people losing healthcare benefits. In addition, Burns and Liu (2017) argue that market mechanisms introduced into healthcare pushed up medical costs, making both LIS and GIS difficult to maintain. To address these challenges, China merged the GIS and the LIS, creating the Urban Employee Basic Medical Insurance (UEBMI) in 1998. This new scheme extends medical coverage not only to workers in state-owned enterprises or government employees but also to other urban workers.

¹ Based on Naughton (2007), the majority of enterprises were state-owned at that time due to the shift towards public ownership.

² Dib et al. (2008) indicate that the cost typically ranges from 0.5 to 2 percent of each farm household's annual income, depending on the local economic conditions and the expected returns.

³ The rural cooperative system is a form of collective agriculture where farmers worked together, sharing their labour and resources. It also provided essential social services, such as healthcare and education.

To extend healthcare coverage to more people, the government launched the New Rural Cooperative Medical Insurance (NRCMI) in 2002. NRCMI focuses on covering medical services for rural populations. Thus, public health insurance provided coverage to both urban and rural populations. Later, in 2007, the Urban Resident Basic Medical Insurance (URBMI) was introduced. This scheme provided coverage for non-workers in urban areas. Therefore, China has established a modern health insurance system covering both urban and rural areas, as well as employed and non-employed groups. However, disparities still exist among the three schemes. UEBMI is mandatory and offers the highest reimbursement rate. In contrast, URBMI is voluntary, with a moderate reimbursement rate, mainly covering inpatient and serious outpatient treatments. Likewise, NRCMI is voluntary and has the lowest reimbursement rate and coverage⁴.

In addition, as market reforms deepened, private health insurance and private hospitals grew rapidly, catering to those seeking higher-quality healthcare. According to Liu et al. (2006), while these private services offer faster and premium care, they come at a much higher cost than public options.

Since 2009, the Chinese government has implemented further healthcare reforms to expand the insurance coverage rate, control medical costs, and enhance health service accessibility and efficiency. Tao et al. (2020) argue that these reforms significantly increased public health insurance coverage, bringing it to over 95% by 2018. To address the disparity of health insurance for rural and urban residents, the Chinese government started a pilot program aimed at combining URBMI and NRCMI into URRMI (Urban and

⁴ A detailed comparison of the reimbursement coverage rates and funding sources can be found in the introduction section of Chapter 2.

Rural Resident Medical Insurance). By 2021, the unification of URBMI and NRCMI had been largely accomplished across all provinces. These developments improve the health insurance system further. According to the State Council (2016), with this merger, reimbursement rates are standardized by adopting the higher rates from both schemes. Moreover, both urban and rural residents can visit the same designated insurance medical institutions and receive the same level of care. Additionally, a uniform catalog of reimbursable medications and medical services is established. The government also sets unified standards for financing and managing medical insurance funds. These changes ensure that both urban and rural residents receive more consistent and comprehensive healthcare benefits. Furthermore, the merger simplifies administrative management, enabling the coordinated allocation of healthcare resources between urban and rural areas.

Due to the significant changes in health insurance over the past 20 years, it is essential to understand how it affects the population, and, in particular, the elderly and children. Compared to other age groups, the elderly and children are more dependent on healthcare services, which naturally increases their reliance on health insurance. Gabriele et al. (2006) describe healthcare consumption by age as following a 'J-shaped curve,' with costs high in childhood, relatively low in adulthood, and then rising sharply in older age. Because the elderly and children are especially vulnerable to illness and require consistent medical support, stable and reliable health insurance coverage is essential. Consequently, changes in health insurance policies can have particularly significant impacts on these groups.

To this end, we focus on three research areas. Firstly, while traditional Chinese culture often overlooks mental health problems⁵, recent developments in the health insurance system may be starting to address this issue. Particularly since May 2013, policymakers have included serious mental illnesses in public insurance coverage.⁶ In addition, depression is a prevalent disorder among older adults and has been a significant global concern due to its high rates and associated mortality risk. (Abdoli et al., 2022). Consequently, it is necessary to understand how different types of public and private health insurance influence the mental health of middle-aged and elderly individuals. Specifically, this study addresses research questions such as whether different public insurance schemes, like UEBMI, URBMI, and NRCMI, have varying impacts on mental health. We are also examining whether having both public and private insurance leads to better mental health outcomes compared to having public insurance alone. Additionally, our research looks into how transitioning between different types of public insurance affects mental health. Lastly, we investigate whether the merger of URBMI and NRCMI into URRMI has improved the mental well-being of middle-aged and elderly individuals.

Second, in the past, limited medical resources in China have often contributed to inadequate attention to pediatric care.⁷ Unlike countries like the United States, which have specific public insurance programs for children, China does not offer a specific

⁵ This is because, in China, it is generally regarded as a source of shame to have mental health problems in the conventional sense (Xu et al., 2017).

⁶ Severe mental disorders, including schizophrenia, delusional disorder (paranoid psychosis), epileptic psychosis, schizoaffective disorder, bi-directional affective disorder, and mental retardation.

⁷ In 1999, China discontinued its pediatric specialty program (a comprehensive training program for professional pediatricians), resulting in only 118,000 pediatricians nationwide, with 0.49 pediatricians per 1,000 children, causing a major shortage in pediatric care (Liu et al., 2022).

health insurance scheme solely for children. Public awareness of pediatric healthcare is still low, and the importance of purchasing health insurance for children has not been investigated. Therefore, it is crucial to evaluate how health insurance affects children's use of medical services. This study focuses on three key research questions. First, what is the relationship between health insurance and healthcare utilization among children in China? Second, how do public and private health insurance differ in their effects on healthcare utilization among children? Finally, does the merger of URBMI and NRCMI into URRMI improve healthcare utilization among children?

Lastly, China is facing a significant increase in its elderly population.⁸ Middle-aged and elderly generally require more medical care, resulting in significantly higher healthcare costs. Han et al. (2020) argue that these increased medical expenses place financial strain on families and add pressure to the public health system. Likewise, Roig (2006) points out that as populations age, healthcare expenditures are expected to rise significantly, creating challenges for the financial sustainability of health systems. Furthermore, International studies have shown that sleep duration and sleep quality are significantly associated with various health conditions, including mental health disorders and cardiovascular diseases (Clayborne et al., 2023; Aneni et al., 2023). Therefore, understanding the impact of some lifestyle factors like sleep habits on medical expenditure is therefore helpful. Our final study thus examines how sleep patterns affect the healthcare costs of the Chinese middle-aged and elderly population. Specifically, we

⁸ China officially became an aging society in 2000, when 7% of its population was over the age of 65 (Han et al., 2020). According to the National Bureau of Statistics (2021), the seventh National Census Bulletin shows this figure had risen to 13.50% by the end of 2020.

address three key research questions: First, we explore the relationship between night-time sleep duration and Out-of-Pocket (OOP) medical expenditures or Catastrophic Health Expenditures (CHE) among this population. Second, we examine how sleep quality influences OOP expenditures and CHE. Third, we assess the role of outpatient visits and hospitalizations in mediating the effect of sleep on OOP expenditures and CHE.

1.2 Structure and contents of the thesis

Three empirical studies are presented in Chapters 2, 3, and 4, respectively. Chapter 2 focuses on the impact of health insurance on mental health for middle-aged and elderly people. Chapter 3 focuses on the impact of health insurance on children's healthcare utilization. Chapter 4 explores the impact of sleep on medical expenditure. Chapter 5 concludes and provides some policy recommendations.

1.2.1 Chapter 2

This paper's primary goal is to examine how three types of public health insurance (UEBMI, URBMI, and NRCMI) and private health insurance affect mental health. Considering that the Chinese government started a pilot program in 2008 to integrate URBMI and NRCMI into URRMI (Urban and Rural Resident Medical Insurance), the second goal of this paper is to investigate the Impact of URRMI on mental health. Our research utilizes the 2011, 2013, 2015, and 2018 waves of the CHARLS (China Health and Retirement Longitudinal Study), which surveys respondents aged 45 and over in 28 Chinese provinces. We find that UEBMI and URBMI have a significant positive effect on the mental health of middle-aged and older individuals, with UEBMI having the greatest impact. In contrast, NRCMI has no significant effects on mental health. The results also

show that people with both public (UEBMI, URBMI) and private health insurance are more likely to have good mental health than those with only public health insurance (UEBMI, URBMI). The result of the time-varying DID model reveals that integrating the urban and rural residents' insurance has a good influence on the mental health of respondents.

1.2.2 Chapter 3

In China, unlike adults who are eligible for the more comprehensive UEBMI, children can only enroll in the URBMI or NRCMI. Given the voluntary nature of URBMI and NRCMI, and the fact that they offer less comprehensive coverage compared to UEBMI, it is crucial to examine the role these insurance schemes play in improving children's access to healthcare services. Due to China's urban-rural disparities, it is also essential to explore the merger policy URRMI that ensures better coverage and healthcare outcomes for this vulnerable population. This analysis could provide valuable insights for policymakers aiming to enhance children's health insurance participation and improve overall access to healthcare in China. Using the 2010, 2012, 2014, 2016, 2018, and 2020 waves of waves of the China Family Panel Studies (CFPS), we investigate how health insurance coverage affects children's healthcare utilization in China. We find that insured children show a 6.5 percentage point higher probability of using healthcare services and a 24.9 percent increase in the frequency of healthcare utilization. Additionally, children covered by public health insurance show a higher probability of using healthcare services than those covered by private health insurance. Furthermore, children covered by public health insurance show a 24.4 percent increase in the frequency of healthcare utilization. By contrast, having private health insurance has no significant impact on the frequency of

healthcare utilization. Finally, the integration of the Urban and Rural Resident Medical Insurance (URRMI) is linked to a higher probability of using healthcare services and increased frequency of healthcare utilization among children.

1.2.3 Chapter 4

The economic impact of medical expenses on a household's financial well-being can be huge, especially in the Chinese context, where reimbursement rates of medical insurance schemes are low. It is therefore necessary to explore the relationship between sleep and healthcare costs in depth. Using data from the 2011 to 2018 wave of the CHARLS database, this paper investigates the impact of sleep duration and sleep quality on Out-of-Pocket (OOP) medical expenditure and the probability of incurring Catastrophic Health Expenditure (CHE). We find a U-shaped association between sleep duration and OOP medical expenditure. Moreover, a negative association is observed between sleep duration and CHE. Specifically, each additional hour of sleep is linked to a decrease of 0.3 percentage points in the probability of incurring CHE. Additionally, better sleep quality is associated with lower OOP medical expenditure and a reduced risk of incurring CHE. Finally, our analysis reveals that the frequency of outpatient visits and hospitalizations serve as mediating variables in the relationship between sleep duration/sleep quality and OOP/CHE. Notably, the frequency of outpatient visits has a more substantial mediating effect.

Chapter 2 Health Insurance and Mental Health

2.1. Introduction

According to the National Healthcare Security Administration (2022), the number of individuals with public health insurance in China has stabilized at over 95 percent. Nevertheless, private health insurance coverage in China is less than 10 percent. China's public health insurance includes the 1998-established Urban Employee Basic Medical Insurance (UEBMI), the 2002-established New Rural Cooperative Medical Insurance (NRCMI), and the 2007-established Urban Resident Basic Medical Insurance (URBMI). The Chinese government began a pilot program in 2008 to integrate URBMI and NRCMI into URRMI (Urban and Rural Resident Medical Insurance), so as to achieve urban-rural parity. Private health insurance has existed in China since 1999, but its development was extremely slow. Although the government began to encourage its growth in 2009, private health insurance in China is still in its early stages when compared to developed countries.⁹

Due to the deterioration of physical functions, diminished sleep, and some chronic diseases, the mental health of middle-aged and older people needs attention. Benedetti et al. (2008) claim that these problems faced by middle-aged and elderly individuals can easily lead to mental disorders like depression. However, In China, mental health issues of middle-aged and elderly individuals have received little attention. This is because it is

⁹ Choi et al.(2018) argue that since the new healthcare reforms were enacted in 2009, more external factors have emerged that contribute to the expansion of private health insurance. After summarizing a number of articles, the authors conclude that commercial health insurance in China is still in its infancy relative to other developed nations.

often considered a source of shame to have mental health issues in the traditional sense.¹⁰ Consequently, it is crucial to investigate how to improve the mental health of middle-aged and elderly Chinese citizens.

There are two ways that health insurance and mental health could be linked. The first is the stress channel. When middle-aged and elderly individuals have health insurance, they are less likely to worry about falling ill, reducing their risk of experiencing stress and mental health issues. Kwon (2009) found that health insurance helps alleviate financial stress among participants. Similarly, Alang et al. (2014) suggest that having health insurance, especially public insurance, can reduce stress in older adults and positively impact their mental well-being. Stress is an important factor in mental health, with chronic stress such as financial or health-related concerns often leading to anxiety, depression, and sleep disturbances, which negatively affect mental health. The second channel is that health insurance provides access to health therapy, resulting in improved mental health. Some research indicates a correlation between health insurance and the utilization of health care. For instance, having health insurance may impact hospital visits.¹¹ Card et al. (2005) also verify that the relationship between having health insurance and increased treatment intensity is positive, resulting in better health outcomes. In some countries, health insurance also covers mental health counseling and therapy. Although mental health treatment in China has faced developmental challenges,

¹⁰ Xu et al. (2018) argue that Individuals are expected to suppress their emotions in traditional Chinese culture, which promotes collective harmony. This is why the older generation associates mental illness with stigma and passes this idea down through generations. Chen et al. (2009) also argue that Chinese people in Canada are more averse to seeing a psychiatrist than locals because of a Chinese stereotype that associates mental health problems with moral weakness.

¹¹ Kwon (2009) and Currie et al. (2008) demonstrate a positive correlation between having health insurance and the frequency of visits to the doctor.

common mental health conditions like depression and anxiety have started to be included in insurance coverage in some provinces only after 2020. Furthermore, improvements in physical health can also contribute positively to mental well-being. This study focuses on the following research questions:

Firstly, do public and private health insurance affect the mental health of middle-aged and older persons? There are considerable differences among public health insurance types in terms of reimbursement rates, coverage, and accessibility, which may influence mental health through mechanisms such as financial stress and varying levels of access to medical services. For example, UEBMI and URBMI differ significantly in design. UEBMI generally provides higher reimbursement rates and more comprehensive coverage, reducing out-of-pocket costs and financial stress for urban employees. In contrast, URBMI, aimed at rural and non-employed urban populations, offers lower reimbursement rates and limited coverage, increasing financial pressure, particularly for major or chronic illnesses. These disparities may indirectly influence mental health by affecting financial stability and access to essential healthcare services.” Despite the high coverage of public health insurance in China, there are some limitations, such as the exclusion of many imported drugs from health insurance reimbursement, a limited choice of medical services, and reimbursement ceiling restrictions. As a result, the role of private health insurance as a supplement becomes more important. Thus, does having some kind of public health insurance with or without private health insurance have a different impact on the mental health of middle-aged and older adults?

Secondly, in general, the UEBMI benefits are superior to the URBMI benefits, and the URBMI benefits are superior to the NRCMI benefits. So, our second question is whether different public health insurance schemes, such as UEBMI, URBMI, and NRCMI, affect mental health differently.

Thirdly, the type of public insurance sometimes changes due to changes in employment or transfers between rural and urban areas. Our third question is, how does the switch between different types of public health insurance affect the mental health of middle-aged and older adults?

Finally, the government has been piloting the merger of URBMI and NRCMI into URRMI since 2008 in order to promote equity in health insurance for rural and urban residents. This merger provides equal access to healthcare and expands reimbursement coverage, which could reduce financial stress and improve access to medical treatment. By easing healthcare access and alleviating financial concerns, the URRMI merger may positively impact mental well-being. This leads us to our final question: Does the government's trial merger of URRMI enhance the mental health of middle-aged rural and urban residents?

Our research fills in gaps in the existing literature.

Firstly, some of the papers on public health insurance in China are primarily focused on the effects of physical health. For example, . Liu et al.(2016) explore health equity issues among UEBMI, URBMI, and NRCMI. However, the majority of the article is devoted to physical health outcomes, with only a brief discussion of mental health. The few articles that are solely concerned with the effect on mental health examine only the NRCMI. For

instance, Qi et al. (2022) and Ma and Oshio (2020) indeed focus on the impact of public health insurance on mental health, but they only explore NRCMI, ignoring the effect of UEBMI and URBMI. Our contribution is a comparison of the mental health effects of the three types of public health insurance (UEBMI, URBMI, and NRCM). It is crucial to look into the effect of all types of public health insurance, as this will allow for a comparison of the various types of insurance on mental health. Then, we can discover mental health inequities and urban-rural inequities.

Secondly, the influence of private health insurance on mental health in China has been neglected in the literature. There are even relatively few empirical papers in the literature comparing private and public health insurance in China. Our contribution in this paper is to compare the effects of private health insurance and public health insurance on mental health.

Thirdly, to the best of our knowledge, only one paper explores the impact of the transitions from UEBMI to URBMI and from UEBMI to NRCMI on chronic patients' mental health (Li and Yuan, 2019). Our contribution is to explore the impact of six transitions of various public health insurance on mental health using panel data in four waves.

Last but not least, we are the first to examine the mental health impact of the merger of the NRCMI and URBMI into the URRMI. This policy has become increasingly important in China in recent years in order to promote equity between urban and rural areas. The impact of this policy on mental health should also be investigated.

The remaining sections of the chapter are organized as follows. In Section 2.2, we present the background of public and private health insurance in China. In Section 2.3,

we examine the literature on the impact of public health insurance and private health insurance, and highlight our contribution. In Section 2.4, we present our hypotheses. Section 2.5 describes our models. The data description is presented in Section 2.6. The regression results are discussed in Section 2.7. Section 2.8 concludes.

2.2 Background

2.2.1 Public Health Insurance in China

China's public health insurance comprises UEBMI, URBMI, and NRCMI. UEBMI covers both active and retired city employees, and costs are shared proportionally between the employee and the employer. From city to city, the contribution rate and amount vary slightly. UEBMI is obligatory, unlike other health insurance plans. The URBMI is voluntary and covers the urban unemployed, students, senior citizens, the disabled, and so on. The premiums are typically less than those of UEBMI and are paid voluntarily by families with appropriate government subsidies. The preceding two types of insurance are for the urban population, whereas the NRCMI is primarily for the rural population and is funded by individual contributions, support from collectives (such as village collectives), and government subsidies. Specifically, the proportion of contributions from collectives and the government provides corresponding subsidies according to local financial capacity. Depending on these local financial conditions, the premiums range between 100 and 500 RMB (Meng and Tang, 2010). Premiums vary depending on local conditions, and

while reimbursement rates show slight regional differences, each type of insurance maintains a generally similar range of coverage. Specific details are as follows:

In general, the reimbursement ratio of UEBMI is slightly higher than the other two types of insurance. Specifically, these three types of insurance have thresholds (deductible line) and maximum limits (capped line). According to the National Healthcare Security Administration (2019), under the NRCMI, the outpatient reimbursement ratio is 35%-50%, and there is a maximum limit of 3,000 yuan. The reimbursement ratio for hospitalization is 55%-75%, and the maximum limit is 180,000 yuan. Under URBMI, the outpatient reimbursement rate is only 50%, and the maximum limit is 2000 yuan. The reimbursement rate for hospitalization is 70%, and the maximum limit is 170,000 yuan. In UEBMI, the reimbursement ratio for outpatient clinics is 70%-90%, and the maximum limit is 20,000 yuan. The reimbursement ratio for hospitalization is 85%-97%, and the maximum limit is 200,000 yuan. Overall, the percentage of hospitalization reimbursement is higher than the percentage of non-hospitalization reimbursement. The comparison clearly shows that the UEBMI is significantly better than the other two types of insurance.

In order to address the issue of equity in access to health care for rural and urban residents, different municipalities have started piloting the merger of the NRCMI and URBMI into the URRMI. According to the State Council (2016) on the Integration of Urban and Rural Residents Basic Medical Insurance System, the merger will allow rural residents to enjoy the same access to health care as urban residents. URRMI maintains a reimbursement rate for hospitalization expenses of approximately 75%. The medical

insurance reimbursement drug catalogue and medical services catalogue will be identical for both urban and rural residents. The pace of implementation of this policy varies greatly from region to region, as the situation varies. In the regions where the policy is being implemented, URRMI is the only renewal option for people who are not attending UEBMI (State Council, 2016). Participation in URRMI is voluntary, and individuals have the option to join or not.

China's public health insurance is committed to providing more reimbursable medications for patients with mental illness. In May 2011, the "Opinions on Issues Concerning the Universal Development of Urban Residents' Basic Medical Insurance Coordination" (Renshebu Fa [2011] No. 59) clarified that outpatient expenses such as maintenance treatment of drugs for severe mental patients should be included in the scope of payment by the insurance fund. Enjoying the hospitalization reimbursement ratio greatly reduces the burden of outpatient expenses for patients with severe mental disorders. The Mental Health Law that came into effect on May 1, 2013, also clearly states that the medical expenses of patients with mental illness can be compensated by basic medical insurance and further promotes mental health services. Various provinces and cities reimburse up to 90% of inpatient and outpatient services for people with six serious mental illnesses. This protects the rights of people with mental illness, reduces their mental stress and financial burden, and promotes the mental health of Chinese people.

The percentage of public health insurance coverage has increased year over year, as reflected in Figure 2.1 and Figure 2.2. We can see in Figure 2.1 that in 2011, public health

insurance only covered 473.43 million people. By 2021, this figure grew to 1364.24 million people. This decade has seen a tripling in the number of people with public health insurance. From Figure 2.2, we can also observe a dramatic increase in health insurance coverage, from 35% in 2011 to 96% in 2018, and ongoing stability above 96% from 2019 to 2021.

2.2.2 Private Health Insurance in China

Liu (2010) argues that the level of private health insurance development in China is not high. In 2008, only 5% of medical costs were reimbursed by private health insurance. Although private health insurance began in China in 1999, there were only two major commercial insurance companies, and industrial growth was slow. When the Insurance Law was changed in 2003, allowing insurance companies to operate short-term health insurance, the number of insurance businesses increased. The Health Insurance Administration Measures were enacted in 2006, and some specialist health insurance businesses were established. The government began to stimulate the development of private health insurance with the implementation of the new health care reform in 2009. Since then, commercial health insurance has grown and begun to witness some changes. In 2016, China, for example, implemented tax-advantaged health insurance. The share of income from the purchase of specific health insurance is deducted at RMB 2,400 per year before paying personal income tax under the Shanghai tax-advantaged health insurance (Choi et al., 2018).

Medical insurance, critical illness insurance, income protection insurance, and long-term care insurance are currently available in China as private health insurance. Medical insurance covers a larger range of disorders, whereas critical illness insurance is for life-threatening illnesses. Income protection insurance is based on the loss of income due to an accident or illness. Long-term care insurance provides care and financial recompense to persons who are disabled or elderly.

Insurance penetration rate (premium to GDP ratio) and insurance density (insurance premium divided by total population) are major indices of insurance development (Okonkwo and Eche, 2019). China's commercial health insurance has a low insurance penetration and insurance density, indicating that the country's commercial health development is still in its early stages. Figure 2.3 shows the change in private health insurance premiums in China over the 10 years from 2011 to 2021. Figure 2.4 and Figure 2.5 show the changes in private health insurance penetration rate and density over the ten years.

As shown in Figure 2.3, between 2011 and 2021, commercial health insurance premiums increased by more than ten times, from a modest 69,172 million yuan (approximately 9540.97 million US dollars) in 2011 to 844,700 million yuan (approximately 116,510 million US dollars) in 2021. Nonetheless, as shown in Figure 2.4, the private health insurance market in China is still not well developed, as the insurance penetration rate was still only 0.7% in 2021, despite increasing over sevenfold over the past decade. Combined with Figure 2.5, we can also see that insurance density, even though it has also increased more than ten times, only reached 584.88 yuan (approximately 80.67 US

dollars) by 2021. According to Insurance Europe (2021), the penetration rate of private health insurance in Europe has already reached 1.01%, while the insurance density has reached 286 euros (equal to about 280.39 dollars), which is more than three times that of China.

2.3. Literature Review

2.3.1 Evidence from the U.S.

There is some research on the impact of public health insurance on mental health in the US.

McMorrow et al. (2017) explore the effect of Medicaid (public health insurance) expansion on low-income parents' mental health. The mental health of parents with children and low incomes deserves more attention because they are under more stress. As of 2010, over ten million parents are uninsured, and the 2010 Affordable Care Act (ACA) aims to minimize the number of low-income individuals without health insurance. Data for the study are obtained from the National Health Interview Survey (NHIS) 2010-2015. Adults aged 19-64 years with minor children are considered. The authors classified their sample into two categories: expansion states and non-expansion states. Expansion states include the 26 states that expanded Medicaid by April 2014, while the rest are classified as non-expansion states. A DID (difference-in-differences) model is used to assess changes in the mental health of low-income parents in expansion states and non-expansion states before and after the 2014 Medicaid expansion. The results indicate that the ACA's 2014 Medicaid expansion had a significant impact on insurance coverage for

low-income parents. Between 2013 and 2015, parental uninsurance rates decreased by 13.0 percentage points in expansion states and by 10.6 percentage points in non-expansion states. The article classifies public health insurance expansions into three categories: small expansions, medium expansions, and large expansions. The findings suggest that large-scale and medium-scale expansions are significantly associated with a reduction in severe psychological distress. This improvement in psychological distress is largely driven by the enhanced affordability and financial security provided by Medicaid coverage, which reduces the stress associated with paying for healthcare expenses. Further, large-scale expansions are associated with increased levels of mental health. That is, public health insurance extensions have an improved effect on the mental health of low-income parents. This paper has some limits. To begin with, the estimation of the low-income population may be inaccurate. This is because all income is self-reported, which may be influenced by memory and social expectations. Second, the time is restricted as only 2015 is used after the policy's implementation, and the influence of the public health insurance expansion on mental health is not immediate for certain parents. As a result, monitoring the effect over an extended length of time is still required.

Fry and Sommers (2018) also examine the effect of public health insurance expansion on the mental health of depressed patients. Random digit dialing is used to collect data from low-income persons under the age of 65 in three different states as part of this study. The three states comprise two expansion states and one non-expansion state. The survey spans the years 2013 to 2016. Nearly 5,000 participants are included in the trial after being diagnosed with depression by a health questionnaire. The results reveal that public health insurance expansion is significantly associated with a decrease in the

proportion of adults with depression. The results indicate that public health insurance expansion reduces the proportion of adults without health insurance by 23%. Furthermore, the percentage of those who delay treatment for depression because of high costs also decreased by 16%. The proportion of people who could not afford depression treatment because of the cost decreased by 18%. In conclusion, the findings reveal that public health insurance expansion increases depressed individuals' access to therapy, thus lowering the rate of depression. However, this article also has some limitations. First, the sample size is relatively small because this survey only contains three states. The results in the three states may not be representative of trends across the country. Another disadvantage of this study is the low response rate of only 22% of the questionnaires.

McInerney et al. (2020) claim that expanding health insurance has no significant impact on mental health. This paper focuses on changes in the mental health of near-elderly people aged 50 to 64 years in the context of health insurance expansion. The database used is the Health and Retirement Study (HRS) from 2010 to 2016. The authors use difference-in-differences models to compare changes in outcomes before and after health insurance expansion in treatment (expansion) and control (non-expansion) states, with a sample that includes more than 3,000 low-income people. Even though the results of the empirical study show that the expansion of health insurance does not affect mental health, health insurance has a significant effect on physical health. This could be because people in this age group are more likely to use health insurance for physical rather than psychological reasons.

Before the Affordable Care Act (ACA), Medicare Part D was one of the largest public insurance expansions. The Part D program is created to expand prescription drug coverage, improve prescription medication utilization, and lower out-of-pocket expenditures for seniors. The Medicare coverage group is the elderly and non-elderly people with long-term disabilities. The mental health of these groups is of great concern. Ayyagari and Shane (2015) investigate the impact of the Medicare Part D program on mental health. These authors also uses a difference-in-differences approach to analyze the impact of the Medicare Part D program, enacted in 2006, on depression. The dependent variable in this study is a dummy variable of depression. The depression is measured using a simplified version of the CESD scale, an 8-item censored version based on the 20-item CESD scale. The Health and Retirement Study (HRS) provides the data for this paper. The HRS is a longitudinal survey conducted on a nationally representative sample. However, HRS does not offer extensive data on prescription drug use or cost. Therefore, the authors use the Medical Expenditure Panel Survey (MEPS) as a supplement to determine the mechanisms by which Medicare Part D may affect psychological health. This study analyses the data from antidepressant use, psychiatrist visits, and psychological treatment to investigate the mechanics of Medicare Part D's effects on mental health. The paper uses data from 2000 to 2010 since the Part D program was implemented in 2006. The sample includes individuals aged 60 to 70 to ensure that the control and treatment groups are comparable. The study's findings reveal that the implementation of Medicare Part D considerably enhances the mental health of elderly people. Specifically, approximately 15% of older persons report a reduction in depression symptoms following the implementation of Medicare Part D.

Based on empirical evidence, increases in antidepressant use and decreases in out-of-pocket costs are associated with the implementation of Medicare Part D. On this basis, increased antidepressant use and lower healthcare costs may be the mechanisms through which Medicare Part D can enhance psychological health. One weakness of this paper is that the data are from two databases. Using data from two databases makes it difficult to evaluate whether antidepressant use or a reduction in financial stress has a greater impact on mental health.

According to Hamersma and Ye (2021), the influence of public health insurance on mental health may vary depending on gender. The National Survey of American Families (NSAF) provided the data for this study. This database conducts three-year surveys of low-income families in 13 states in the United States in 1997, 1999 and 2002. This survey covers a broad age range, beginning with children as young as age 0. However, this study excludes children under the age of five due to a lack of data on mental health. Finally, over 30,000 minors are selected for the survey. The dependent variable, mental health, is measured using the Behaviour Problems Index score, which consists of six age-specific items. The findings indicate that expanding public insurance coverage significantly affects both boys' and girls' mental health improvements, but boys' improvements are more pronounced. This could be due to the fact that boys and girls suffer different types of psychological problems, and different psychological problems are not equally covered by public health insurance. Therefore, access to psychological care through public insurance has a varied impact on the mental health of boys and girls. One factor that may affect the accuracy of the results is that some of the assessment questionnaire's

items about mental health outcomes are answered on behalf of the children by their guardians.

While the above studies focus only on public health insurance's impact on mental health, the following studies examine the effects of both public and private health insurance on mental health.

DeRigne et al. (2009) examine the impact of public and private health insurance on unmet mental health needs in the United States. They use logistic regression models to examine the impact of children's health insurance status on their unmet mental health needs. The study uses data from the 2011 National Survey of Children with Special Health Care Needs (NSCSHCN). This study's sample includes 10,675 children who are screened for mental health disorders described by parents as emotional difficulties and other mental health problems. The study's findings indicate that children with health insurance are approximately three times less likely to have unmet mental health needs than children without health insurance. Additionally, children with just public health insurance are about one-fifth as likely as children with only private health insurance to have unmet mental health needs. Finally, children who have both public and private health insurance are around 35% less likely to have unmet mental health needs than children who only receive private coverage. This implies the critical role of health insurance, particularly when public health insurance combines with private health insurance, in supporting children's mental health requirements. The paper's limitation is its reliance on parental reports of children's mental health needs. Parents may

underreport their child's mental health status. As the data are less accurate, the reliability of the empirical findings may be partially diminished.

Rowan et al. (2013) evaluate the disparities in mental health status between 1999 and 2010 across three insurance states (publicly insured, privately insured, and uninsured). The Kessler-6 scale classifies mental health into three categories: no mental health problems, moderate mental health difficulties, and severe mental health problems. The authors divide data into six groups based on 2-year intervals: 1999-2000, 2001-2002, 2003-2004, 2005-2006, 2007-2008, and 2009-2010, to allow for comparisons of changes in mental health status among health insurance states. This paper examines adults aged 18 to 64 using the Integrated Health Interview Series (IHIS) data. According to empirical results, every two years, the proportion of patients with moderate mental illness who have public insurance has risen, whereas the number who have private insurance has fallen. The reason for this is that people with mental health problems do not have easy access to positions where employers offer private health insurance. According to this study, those with public insurance are more likely to receive expert psychological treatment than those with private insurance. The study's findings imply that for those with mental health difficulties, public health insurance is often more important than private insurance. The reason for this is partly due to the fact that people with public health insurance have more disabled people and receive more benefits. The main limitation of this study is that we do not know whether mental health therapies are covered by each type of health insurance. It is also necessary to do a more detailed

analysis of the influence of specific features of distinct types of health insurance on access to services and costs. Another shortcoming of this paper is that it may underestimate the use of mental health services. Because psychotherapy is integrated into the general health care system in some areas of the United States, some use of psychological services is recorded as general health care.

Ward and Martinez (2014) investigate the effect of varying health insurance coverage on psychological distress among U.S. adults. The article makes use of National Health Interview Survey data from 2001 to 2010. Participants' health insurance status falls into the following categories: no health insurance, private health insurance, public health insurance, and a change in health insurance status. In this paper, the K6 scale is also used to measure psychological stress. The results indicate that adults with private or no health insurance are less psychologically distressed than those with public or other health insurance. The reason for this could be that having private health insurance, possibly due to better employment and more income, is related to better mental health than having public insurance or no insurance. According to the descriptive statistics, those with private health insurance in the United States experience the least amount of stress. The recent transition from being uninsured to having health insurance (i.e., gaining insurance) is associated with greater distress than losing health insurance. In other words, recent insurance acquisition is associated with a rise in psychological distress. This may result from beginning a new job because employers typically provide new private health insurance. Moreover, new employees can face significant stress. Sometimes, obtaining private insurance signifies the beginning of a new job. In addition, joining a public health insurance program such as Medicaid may be due to recent unemployment or disability.

Both of these circumstances could increase an individual's emotional stress. The K6 scale has a 30-day reference period, which is a limitation of the study as it is impossible to determine if a change in a person's health insurance status occurred within or near this 30-day reference period.

Alang et al. (2014) investigate the relationship between health insurance status and psychological distress among people with disabilities. The data for this paper come from a comprehensive health interview series from 2008 to 2010. The results of the study show that people with disabilities who are uninsured are more likely to experience psychological distress than those with health insurance. People with public insurance have less psychological distress than those with private health insurance. This could be because public insurance provides more comprehensive benefits, such as access to medical equipment, than most private insurance. Overall, the results imply that having health insurance, especially public health insurance, can improve the psychological distress of people with disabilities. This article has a limitation in that the authors do not consider the severity and type of disability, which may compromise the accuracy of the results.

In conclusion, the above articles demonstrate the effect of public health insurance on the mental health of children and adults, with the majority of studies indicating a positive effect of public health insurance on mental health and a small number of articles claiming that public health insurance has little effect on mental health (McInerney et al., 2020). There are also some articles comparing the mental health effects of private health insurance and public health insurance. The results indicate that public health

insurance has a more positive effect on mental health for individuals with mental illness or physical disability (Alang et al.,2014; Rowan et al.,2013), whereas private health insurance reduces mental stress for all U.S. adults (Ward and Martinez, 2014). Another research argues that when public health insurance is accompanied by private health insurance, unmet mental health needs are reduced by 35% (DeRigne et al.,2009).

2.3.2 Evidence from China

Fan et al. (2019) investigate the effects of URBMI (Urban Resident Basic Medical Insurance) and NRCMI (New Rural Cooperate Medical Insurance) on health. Health is measured here using three dimensions: chronic illness, self-reported health, and life satisfaction. Chronic illness and self-reported health are used to measure physical health, while the question of life satisfaction measures mental health. This study uses data from five waves of the China Health and Nutrition Survey (CHNS) between 2004 and 2015. The sample comprises 18,155 respondents. An endogenous treatment effect model is used to infer the causal effect of public health insurance on mental health. Based on the findings of the empirical testing, it is possible to conclude that public health insurance has a positive impact on the mental health of the covered. Furthermore, URBMI is more effective than NRCMI in promoting mental health. This outcome could be attributed to URBMI's higher reimbursement rates and reimbursement caps than NRCMI. In addition, URBMI reimburses for all inpatient and some outpatient services. However, NRCMI reimbursement does not cover any outpatient services. The results also indicate that

public health insurance is highly associated with higher health service utilization. In addition, there is evidence that those with public health insurance are more likely to engage in healthy lifestyle behaviors such as physical activity. Finally, the study discovers that having public health insurance lowers out-of-pocket costs for health care. These findings imply that public health insurance influences mental health through increased healthcare utilization, lower out-of-pocket costs, and healthy lifestyle practices. One limitation of this article is that respondents with UEBMI have been excluded, so the comparison of public health insurance seems to be incomplete. Another limitation is that mental health is only evaluated based on life satisfaction, which is inaccurate. Because different people have different personalities, and some may be ambitious and dissatisfied with their current lives, this does not actually prove that they are not in good mental health.

Liu et al. (2016) explore health inequity issues in different public health insurance schemes. The main independent variables are three types of insurance, including UEBMI, URBMI, and NRCMI. The dependent variables include self-reported health status and mental health. Mental health is assessed by the Worry Degree Scale. This research uses data from the National Survey of Aged Population in Urban/Rural China from 2006 and 2010. This database contains information about elderly people aged 60 and over in twenty provinces of China. A sample of 1,000 people is drawn from each province. Finally, in 2006, there are 19,947 respondents, and in 2010, there are 19,986. Multiple linear regression is used to investigate the impact of various insurance types on mental health while controlling for other social determinants. The findings indicate that the UEBMI participants have a superior mental health state and self-reported health status than the

other three groups (URBMI, NRCMI, and Uninsured). This could be due to UEBMI's more comprehensive coverage and greater access to healthcare resources, which reduces financial and healthcare-related stress, thereby alleviating psychological distress. Additionally, NRCMI participants' mental health status is 0.081 units better than that of URBMI participants and 0.092 units better than that of individuals without health insurance. In contrast, URBMI users have more excellent self-reported health than NRCMI participants and uninsured individuals. The disparities in mental health outcomes across the three types of public health insurance reflect differences in coverage levels and access to healthcare resources, which are an important channel through which insurance influences mental health. Therefore, new policies for NRCMI and URBMI should be implemented to support participants' mental health. For example, increasing the amount of mental prescription medication. This paper has one limitation: the data are not a panel. This makes determining the causal relationship between public health insurance and mental health could be difficult.

Qi et al. (2022) explore the effect of NRCMI on farmers' subjective well-being (SWB). The data for this study came from the China General Social Survey (CGSS) in 2017. This research is centered on the agricultural sector, and thus, only data entries corresponding to agricultural hukou have been included, resulting in a total of 7,743 observations. The dependent variable, subjective well-being (SWB), is a dummy variable. SWB is assessed by one question in CGSS (2017). The independent variable, NRCMI, is also a dummy variable. The results show that participating in NRCMI significantly increases the farmers' subjective well-being. Some control variables, such as education, marital status, and physical health, are positively related to SWB. Other control variables, such as religion,

children, and political party, are negatively related to mental health. Further results indicate that engagement in NRCMI appears to benefit farmers' subjective well-being by improving their total consumption levels. As NRCMI participants do not need to set aside money for unforeseen health issues, they can boost their spending in other areas to improve their subjective well-being. Using an instrumental variable estimator to control for endogeneity issues, the authors find that participation in the NRCMI still significantly improves farmers' subjective well-being. The article's main limitation is that subjective well-being is measured by only one question. The results may be biased because human emotions are always complex and difficult to evaluate with a single question.

Ma and Oshio (2020) investigate the health effects of the NRCMI. The two independent variables related to mental health in this study are 'mental health outlook' and 'current mental health.' The data are based on three waves of longitudinal data from the China Health and Retirement Longitudinal Study (CHARLS), collected in 2011, 2013, and 2015. There are 32,808 total samples in this study. The study examines rural middle-aged and older adults aged 45 and over. The author divides the ages into three categories: 45-49, 60-64, and 65 and older. According to the empirical findings, the NRCMI has a positive link with future mental health but has no statistically significant effect on current mental health. Participants in the NRCMI are required to pay for their own medical care when they visit a doctor and are reimbursed over time; this may explain why the NRCMI has no impact on mental health at present but has a positive impact on mental health in the future. It is possible that the NRCMI's shortcomings also explain why it does not affect present mental health. For instance, the NRCMI does not reimburse the cost of outpatient visits and covers fewer types of fatal illnesses than the UEBMI. There are

several issues with this article. The only question used to assess current mental health is "How often have you felt down recently?" In addition, the future mental health assessment consists of a single question: "How often do you feel optimistic about the future?". Measuring complex and dynamic psychological issues with a single question is insufficiently precise.

Li and Yuan (2019) explore the impact of public health insurance transition on chronic patients' mental health. Since China's public health insurance system is commonly tied to employment status, health insurance transitions are frequently triggered by unemployment or migration to urban regions. The data for this study come from the China Health and Retirement Longitudinal Study (CHARLS 2015), which provides information on respondents' insurance status between 2013 and 2015. This survey includes roughly 12,400 households. The study examines participants who are enrolled in the UEBMI in 2013 but are forced to switch to the other two health insurances owing to unemployment in 2015. Therefore, the independent variables are the transitions from UEBMI to URBMI and from UEBMI to NRCMI. According to empirical evidence, there is a significant increase in mental health problems among people with chronic conditions who transition from UEBMI to NRCMI. However, the impact of the transition from UEBMI to URBMI on mental health is not significant. When patients with chronic illnesses transition from UEBMI to NRCMI, they experience an increase in psychological problems. This may be because NRCMI benefits are less favorable, and medical care is better in urban hospitals. In comparison, the transition from UEBMI to URBMI would not increase psychological problems for chronic patients. It is likely that because both are health insurance plans in urban areas, there is little difference in the impact on the ease of

access to health care for people with chronic conditions. One limitation of this paper is that it only uses the 2015 wave of the CHARLS. Another limitation is that only two transformations have been explored (UEBMI to URBMI and UEBMI to NRCMI). If more transitions are taken into account, the results will be more comprehensive.

Tian et al. (2012) investigate the effect of public health insurance on depression in Northwest China. This study includes three waves of data from 2006 to 2008. More than 4,000 people are chosen from two cities in the northwest. The CES-D questionnaire is used to evaluate mental health in this survey. Ordinal regression is used to examine the relationship between depression and health insurance. According to the data description, approximately one in every five people suffers from severe depression symptoms. According to the regression results, public health insurance plays a favorable and significant role in depression. Furthermore, people who do not have public health insurance have a higher risk of developing more severe depressive symptoms than those who do. One possible explanation is that having public health insurance provides a sense of security, which might alleviate the stress of medical care. Few studies have focused on depression in Northwestern China. This survey reveals the high prevalence of depression in Northwestern China and shows the significant role of public health insurance for depression in this area. However, this research has several drawbacks. Firstly, the authors chose only two cities within a single province. The statistics will be more representative if multiple cities in different provinces are chosen. Secondly, a significant limitation of this analysis is its failure to categorize public health insurance for discussion. The study simplifies the complexity of public health insurance by merely focusing on general trends and overall impacts.

In conclusion, most studies find that public health insurance has a positive effect on mental health. However, some studies find that public health insurance (NRCMI) has no significant effect on mental health (Ma and Oshio,2020; Ma,2022). In addition, there are no studies on the impact of private health insurance on mental health in China.

2.3.3 Gaps and Contributions

Several studies have examined the effects of public health insurance on mental health in China.¹² However, there is a lack of literature comparing the mental health effects of the three types of public health insurance with those of private health insurance. Most authors have overlooked the role of private health insurance for mental health. There are no empirical studies on the effects of private health insurance on mental health in China. No articles have examined whether there are differential effects on mental health when public health insurance is accompanied or not accompanied by private health insurance. The contribution of this chapter is to compare the effects of different types of public and private health insurance on mental health. It also explores the differences in the effects on mental health when public health insurance is accompanied or unaccompanied by private health insurance. As we mentioned in the background section,

¹² Tian et al. (2012) investigate the effect of public health insurance on depression in Northwest China. Qi et al.(2022) and Ma and Oshio(2020) only focus on the mental health impact of NRCMI.

both the insurance penetration and private health insurance density in China are increasing. This means that more and more people are using private health insurance, so it is important to pay more attention to private health insurance.

Secondly, as far as we are aware, there are no empirical studies investigating the mental health effects of the merger of urban and rural resident health insurance. Our contribution is to explore the effect of combining URBMI and NRCMI into URRMI on mental health using a DID model. In recent years, China's URRMI is a major reform initiative aimed at promoting equity between urban and rural populations. As an increasing number of urban and rural individuals begin to be covered by the URRMI, it is essential to investigate the URRMI's effect on mental health.

Thirdly, to the best of our knowledge, only one paper used the 2015 wave of the CHARLS to explore the impact of transitions from UEBMI to URBMI and from UEBMI to NRCMI on chronic patients' mental health (Li and Yuan, 2019). Our contribution is to explore the impact on the mental health of six transitions of various public health insurance using four waves of the CHARLS, and focusing on all respondents, not just those with chronic disease.

2.4. Hypotheses

In previous literature, most research argues that health insurance plays a significant and positive role in mental health. In China, there are different types of public health insurance, namely the UEBMI, the URBMI, and the NRCMI. According to a number of research studies cited in the literature review section, Fan et al. (2019) argue that URBMI

and NRCMI are beneficial for promoting mental health. Qi et al. (2022) state that NRCMI can enhance the subjective well-being of farmers. Also, considering private health insurance, our first hypothesis reads:

Hypothesis 1: UEBMI, URBMI, NRCMI, and private health insurance have a positive impact on mental health.

Health insurance can influence mental health in two ways. The first channel is getting treatment. Patients with public health insurance would be able to receive mental health therapy and, as a consequence, improve their mental health. Rowan et al. (2013) argue that patients with mental illness who have access to public health insurance are more likely to receive expert therapy. Ayyagari and Shane (2015) also demonstrate that expanding psychiatrist therapy is a mechanism via which Medicare Part D could improve mental health. These findings suggest that public health insurance is critical for providing care for persons who have mental illness. As the background section explains, China's public health insurance is committed to covering more mental disease medications.

The second mechanism is a stress channel. If middle-aged and elderly people have health insurance, they are less likely to be concerned about getting sick. This implies they are less prone to experience stress and mental health issues. According to Kwon (2009), health insurance reduces participants' financial stress. Fan et al. (2019) also argue that public health insurance can reduce people's out-of-pocket medical expenses and relieve financial stress, which can improve people's mental health. Additionally, the findings of Alang et al. (2014) imply that having health insurance, especially public health insurance,

can improve the psychological stress of people with disabilities. Therefore, having health insurance can lessen people's stress and positively affect their mental health.

As a result, we propose that health insurance will benefit mental health. However, there are disparities between these public health insurances, with UEBMI reimbursement rates and caps being higher than the other two types of public health insurance. Liu et al. (2016) argue that UEBMI plays the most important role in mental health. The findings of this research indicate that the UEBMI participants have a superior mental health state than the other three groups (URBMI, NRCMI, and Uninsured). Therefore, we propose the second hypothesis:

Hypothesis 2: The positive effect of UEBMI on mental health is greater than that of URBMI on mental health, and the positive effect of URBMI on mental health is greater than that of NRCMI on mental health.

Due to the discrepancies between the various types of public coverage, the NRCMI and URBMI gradually merged into the URRMI to achieve parity between urban and rural areas. The merger of urban and rural residents' basic medical insurance implies that rural people can enjoy the same benefits as urban residents. All reimbursement standards are now based on the higher standards as a result of the merger (State Council, 2016). The number of medical insurance-designated hospitals for rural residents and urban residents has grown, making it flexible to see a doctor (Tan et al., 2019). In addition, the percentage of reimbursement and the scope of drug reimbursement have also increased, so the amount of out-of-pocket medical expenses have been relatively reduced (Xie et

al.,2019). Furthermore, URRMI supports mental health through two primary channels. The first channel is stress relief: the increased coverage and benefits provided by URRMI help alleviate health-related financial concerns. The second channel is access to treatment: following the insurance merger, reimbursement rates have increased, and the number of designated hospitals has expanded, reducing barriers for patients across urban and rural areas. This improvement enhances accessibility to healthcare services. Therefore, the influence of both stress relief and treatment accessibility channels in connecting health insurance and mental health is strengthened through URRMI. Therefore, we predict that the URRMI will have a significant positive effect on people's mental health. In other words:

Hypothesis 3: The emergence of URRMI (Urban Rural Resident Medical Insurance) is conducive to promoting mental health.

2.5. Specifications and Methodology

2.5.1 Baseline Model

To test Hypotheses 1 and 2, we construct a baseline model based on (Beck,2020) and (Sato et al., 2020). Our dependent variable, good mental health, is a dummy variable, with 1 representing good mental health and 0 representing poor mental health. We use the CES-D-10 to measure mental health (Aslanidis et al., 1996; Dahl et al., 1999). All questions of the CES-D 10 form can be found in Figure A2.12 in the Appendix. The 10 questions have 8 negative questions and 2 positive questions. For negative questions, the response options "<1 day," "1~2 days," "3~4 days," and "5~7 days" are coded by the

numbers 0, 1, 2, and 3. We utilize backward scoring for the two positive items ("hopeful for the future") and ("I am happy"); the response options "<1 day," "1~2 days," "3~4 days," and "5~7 days" are coded by the numbers 3, 2, 1, and 0. The lowest possible total score is 0, and the highest possible score is 30. The greater the score, the more severe the mental health problem. Most literature uses a score of 10 as the cut-off point (Andresen et al., 1994). A total CESD-10 score ≥ 10 is identified as poor mental health. A CESD-10 < 10 is categorized in the good mental health group. The following is our baseline specification:

$$\begin{aligned} \text{Good_Mental_Health}_{it} = & \beta_1 * \text{NRCMI}_{it} + \beta_2 * \text{UEBMI}_{it} + \beta_3 * \text{URBMI}_{it} + \beta_4 * \\ & \text{Private_Health_Insurance}_{it} + \beta_5 X_{it} + u_i + v_t + \mu_{it} \end{aligned} \quad (2-1)$$

Good_Mental_Health_{it}: It is a dummy variable, with 1 representing good mental health and 0 representing poor mental health for individual *i* at time period *t*. *NRCMI_{it}*: Individual *i* covered by New Rural Cooperative Medical Insurance (NRCMI) at time *t* (0: No, 1: Yes)

UEBMI_{it}: Individual *i* covered by Urban Employee Basic Medical Insurance (UEBMI) at time *t* (0: No, 1: Yes)

URBMI_{it}: Individual *i* covered by Urban Resident Basic Medical Insurance (URBMI) at time *t* (0: No, 1: Yes)

Private_Health_Insurance_{it}: Individual *i* covered by Private Health Insurance at time *t* (0: No, 1: Yes)

This equation also includes a u_i component that captures unobserved heterogeneity, a v_t component, which is a time-specific component that captures business cycle effects, is accounted for by including wave dummies. μ_{it} is an idiosyncratic error.

The control variables (X_i) include:

Gender_i is a dummy with a value of 1 if the responder is male, and 0 indicates female.

The sign of this variable is unclear. Depression and anxiety disorders are more prevalent in women than in men, while substance abuse and antisocial behavior are more prevalent in men. Kiely et al. (2019) study the mental health of older men and women and discover that older women are more likely than older males to suffer from mental health issues such as depression and anxiety. Men and women are exposed to distinct pressures, resulting in disparities in psychological issues.

Age_{it} is the age of the individual i at time t . This variable is expected to have a negative sign on the elderly. Trollor et al. (2007) contend that growing age is connected with a decreased risk of exhibiting mental disease symptoms. Bell (2014) also argues that the negative impacts of aging on mental health tend to exceed the favorable effects, as it appears that psychological distress increases over time. In addition, Farrer et al. (2008) claim that mental disorders are more common in those over the age of 70.

Married_{it} is a dummy that equals 1 if the respondent is married and 0 if not. The majority of renowned papers claim that marriage is beneficial to mental health. According to Vaus (2002), marriage can lower the risk of mental problems in both men

and women. Additionally, Horwitz et al. (1996) believe that marriage is advantageous to mental health. Therefore, the sign of this variable is likely to be positive.

Chronics_{it} : indicates the number of chronic diseases suffered. According to Verhaak et al., chronic disease patients have a greater likelihood of suffering from mental problems. Chapman et al. (2005) also demonstrate a significant correlation between an increase in chronic disease and an increase in mental disorders, particularly depression. Therefore, the sign of this variable is likely to be negative.

Total_Income_{it} indicates the total household income of individual *i* at time *t*. Gresenz et al. (2001) investigate the relationship between family income and mental health issues and discover that lower-income households have a higher likelihood of anxiety or depression than higher-income households. Mentzakis and Moro (2009) explore the relationship between income and subjective well-being (SWB) and find that as income increases, so does SWB. Thus, the sign of this variable should be positive.

illiterate_{it}, *primary_{it}*, *secondary_{it}*, *college_{it}* are all dummy variables indicating the degree of education. For instance, *illiterate_{it}* equals to 1 indicates that individual *i* is illiterate at time *t*, while *illiterate_{it}* equals 0 means that individual *i* is not illiterate. *primary_{it}*, if equal to 1, signifies that individual *i* has completed primary or higher education at time *t*. *primary_{it}*, if equal to 0, indicates that individual *i* has not completed primary or higher education. Accordingly, *secondary_{it}*, if equal to 1, means that individual *i* has completed secondary or higher education at time *t*. *secondary_{it}*, if equal to 0, denotes that individual *i* has not completed secondary or higher education. Additionally, if *college_{it}* is 1, it signifies that individual *i* has a college or higher degree

at time t . If $college_{it}$ is 0, it means that individual i has not have a college degree or higher degree at time t .

According to Cornaglia et al. (2015), the high psychological strain is strongly associated with low educational outcomes and early dropout. Araya et al. (2003) also claim that education and common mental disorders have a significant and negative relationship. As a result, we predict that the sign for $illiterate_{it}$ could be negative and the signs of $primary_{it}$, $secondary_{it}$, $college_{it}$ would be positive.

$Work_{it}$ is a dummy variable having a value of 1 if the respondent is now employed, and 0 if the respondent is currently unemployed or retired. Much research has shown that having a job and having improved mental health are highly linked. For example, Drake and Wallach (2020) demonstrate that employment can enhance mental health and that unemployment can lead to deteriorating mental health, even among those with the most severe mental diseases. Therefore, the sign of this variable is expected to be positive.

$night_sleep_{it}$ is a continuous variable that refers to how long the respondent sleeps at night. Many authors have demonstrated that sleep deprivation is strongly associated with psychological problems (Milojevich and Lukowski, 2016; Lee et al., 2015). Milojevich and Lukowski (2016) explore the relationship between sleep duration and mental health for undergraduate students. The results reveal that sleep duration is negatively associated with some psychological problems. According to research conducted by Lee et al. (2015) on the relationship between sleep duration and mental health in Korean people, both short sleep duration (less than 6 hours) and long sleep duration (more than

9 hours) are strongly associated with increased mental health consultations. So the sign of this variable is unclear.

IADLs/ADLs_{it}: limitations in instrumental and basic activities of daily living (IADL/ADLs). Ormel et al. (2002) find a strong influence of IADL/ADL on depression symptoms in older adults. Gayman et al. (2008) also prove that limitation (IADL/ADL) can influence changes in depression symptoms, but there is no evidence of an opposing relationship. Ahmad (2020) investigate the association between functional limitation (measured by ADL and IADL) and depression in Malaysia, finding that older people with limits in IADL have a nearly two-fold increased risk of having depression, while those with limitations in ADL have a 2.6-fold increased risk of having depression. Therefore, the sign of this variable is expected to be negative.

If Hypothesis 1 and 2 hold, the coefficients of NRCMI, UEBMI, and URBMI are all positive, with UEBMI having the most significant effect.

2.5.1.1 Model Extensions

We extend Model 1 as follows to investigate how the effects on mental health differ when public health insurance is accompanied or not accompanied by private health insurance.

$$\begin{aligned}
 \text{Good_Mental_Health}_{it} = & \beta_1 * \text{UEBMI_noprivate}_{it} + \beta_2 * \text{UEBMI_private}_{it} + \\
 & \beta_3 * \text{URBMI_noprivate}_{it} + \beta_4 * \text{URBMI_private}_{it} + \beta_5 * \text{NRCMI_noprivate}_{it} + \\
 & \beta_6 * \text{NRCMI_private}_{it} + \beta_7 * X_{it} + u_i + v_i + \mu_{it}
 \end{aligned} \tag{2-2}$$

$UEBMI_noprivat_{it}$: A dummy variable with a value of 1 when the individual has UEBMI but no private health insurance. Otherwise 0.

$UEBMI_privat_{it}$: is a dummy variable with a value of 1 when the individual has both UEBMI and private health insurance. Otherwise, it is 0.

$URBMI_noprivat_{it}$: is a dummy variable with a value of 1 when the individual has URBMI but no private health insurance. Otherwise, it is 0.

$URBMI_privat_{it}$: is a dummy variable with a value of 1 when the individual has both URBMI and private health insurance. Otherwise, it is 0.

$NRCMI_noprivat_{it}$: A dummy variable with a value of 1 when the individual has NRCMI and no private health insurance. Otherwise 0.

$NRCMI_privat_{it}$: A dummy variable with a value of 1 when the individual has both NRCMI and private health insurance. Otherwise 0.

X_{it} : are control variables, all control variables remain the same as before.

2.5.1.2 Health Insurance Transitions

In order to explore the impact of the public health insurance transition on mental health, we have the following Model:

$$Good_Mental_Health_{it} = \beta_1 * (Trans_URBMI_NRCMI_{it} / Trans_URBMI_UEBMI_{it} / Trans_UEBMI_NRCMI_{it} / Trans_UEBMI_URBMI_{it} / Trans_NRCMI_URBMI_{it} / Trans_NRCMI_UEBMI_{it}) + \beta_2 * X_{it} + v_i + u_t + \mu_{it} \quad (2-3)$$

$Trans_URBMI_NRCMI_{it}$ is a dummy variable. When this variable equals 1, the individual i switch from URBMI to NRCMI at time t . A value of 0 indicates that individual i keep URBMI unchanged at time t .

$Trans_URBMI_UEBMI_{it}$ is a dummy variable. When this variable equals 1, the individual i transfer from URBMI to UEBMI at time t . A value of 0 indicates that individual i keep URBMI unchanged at time t .

$Trans_UEBMI_NRCMI_{it}$ is a dummy variable. When this variable equals 1, the individual i transfer from UEBMI to NRCMI at time t . A value of 0 indicates that individual i keep UEBMI unchanged at time t .

$Trans_UEBMI_URBMI_{it}$ is a dummy variable. When this variable equals 1, the individual i transfer from UEBMI to URBMI at time t . A value of 0 indicates that individual i keep UEBMI unchanged at time t .

$Trans_NRCMI_URBMI_{it}$ is a dummy variable. When this variable equals 1, the individual i transfer from NRCMI to URBMI at time t . A value of 0 indicates that individual i keep NRCMI unchanged at time t .

$Trans_NRCMI_UEBMI_{it}$ is a dummy variable. When this variable equals 1, the individual i transfer from NRCMI to UEBMI at time t . A value of 0 indicates that individual i keep NRCMI unchanged at time t .

X_{it} denotes all control variables, which are the same as the first Model, including $Gender_i$, Age_{it} , $Chronics_{it}$, $night_sleep_{it}$, $IADL_s$, ADL_s , $Married_{it}$, $Income_{it}$, $Work_{it}$, $Primary_{it}$, $Secondary_{it}$, $college_{it}$

2.5.1.3 Methods

For our baseline models, we choose a linear probability model (LPM) with two-way fixed effects to analyze the relationship between different types of health insurance and mental health. We hypothesize that the relationship between the independent variables (UEBMI, URBMI, NRCMI, and private health insurance) and mental health is linear. The two-way fixed effects approach in the LPM also helps address potential endogeneity concerns, as it controls for unobserved individual-specific traits that remain constant over time (Wooldridge, 2010). By capturing these fixed effects, the model better isolates the impact of health insurance on mental health outcomes. This model is also appropriate given our binary dependent variable, where 1 represents good mental health and 0 represents poor mental health. Although mental health status is binary, we do not choose a fixed-effects Logit model, as it may lead to substantial observation loss when the dependent variable remains constant over time for certain individuals. The two-way fixed-effects LPM avoids this issue by retaining more observations, enabling a more accurate analysis. Additionally, the LPM coefficients can be directly interpreted as marginal effects, making it clearer to understand how changes in health insurance coverage impact mental health (Wooldridge, 2010).

Regarding endogeneity, we acknowledge the potential issue of adverse selection in the relationship between health insurance and health (including mental health), as seen in some contexts (Cutler and Zeckhauser, 2000). Individuals in poorer health may be more likely to obtain insurance due to anticipated healthcare needs, which could bias our estimates. However, in the context of China, this issue is minimized for several reasons. First, mental health services in China are still developing, with many individuals not actively seeking insurance specifically for mental health needs (Liang et al., 2018). Common conditions like depression and anxiety only began receiving limited insurance coverage in certain provinces after 2020 (National Healthcare Security Administration, 2021). Second, over 95% of adults are covered by public health insurance, with UEBMI participation mandatory for urban employees and URBMI and NRCMI widely adopted based on urban or rural residence rather than individual health status. These factors together reduce the potential impact of adverse selection in our analysis.

To further strengthen our analysis, we also use a Correlated Random Effects (CRE) Probit model for robustness. The CRE Probit model serves as a robustness check, capturing random individual-specific effects while avoiding the issue of observation loss commonly seen in fixed-effects models (Wooldridge, 2010; Wooldridge, 2019). By combining the two-way fixed-effects LPM and the CRE Probit model, we provide a more comprehensive analysis of health insurance's impact on mental health. This approach addresses concerns around data retention, interpretability, and robustness.

2.5.2 DID Model

We build a DID model to investigate the influence of the insurance merger policy on urban and rural residents' mental health. The DID model is frequently utilized in health policy research (Wing et al., 2018; Dimick and Ryan, 2014). The DID model can almost eliminate the endogeneity problem by mitigating the bias produced by omitted variables.

A Time-varying DID (also called heterogeneous timing DID) with a fixed effect can test Hypothesis 3 (Beck et al., 2010). In the standard DID model, all individuals in the treatment group begin to suffer policy shock at the same time. In reality, many policies are piloted before being implemented across the country. The time-varying DID model is used in pilot programs in which treatment groups are exposed to the policy shock at different times. As a result, the treatment time dummy variable differs in the Time-varying DID model since the treatment period is not the same for each individual.

The Time-varying DID Model can be expressed as follows:

$$Good_Mental_Health_{it} = \alpha_0 + \alpha_1 Treat_{it} + \alpha_2 X_{it} + v_i + \rho_t + \varepsilon_{it} \quad (2-4)$$

Good_Mental_Health_{it}: It is a dummy variable, with 1 representing good mental health and 0 representing poor mental health.

Treat_{it} is a dummy variable with the value 1 for the treatment group and 0 for the control group.

The treatment group is made up of people who take part in URRMI.

The control group is made up of people who still participate in URBMI or NRCMI but do not participate in URRMI in these four waves. The proportion of the treatment group is 7.88%, whereas the proportion of the control group is 92.12%.

X_{it} denotes all control variables, which are the same as the first Model, including

$Gender_i$, Age_{it} , $Chronics_{it}$, $night_sleepi_{it}$, $IADLs$, $ADLs$, $Married_{it}$,

$Income_{it}$, $Work_{it}$, $Primary_{it}$, $Secondary_{it}$, $college_{it}$

v_i, ρ_t are individual and time-fixed effects. ε_{it} component that captures idiosyncratic error.

The coefficient α_1 should be the focus of analysis in the regression results, as it shows the effect of the integration of urban and rural resident health insurance on mental health. According to hypothesis 3, URRMI (Urban and Rural Resident Medical Insurance) is conducive to promoting mental health. Hence, if hypothesis 3 is satisfied, α_1 should be significant and positive.

2.5.2.1 Event Study Approach (parallel trend test)

Parallel trend testing is crucial for DID model. Time-varying DID model does not have a uniform policy implementation timing, so we cannot do a standard parallel trend plot (the trend in the mean of the treatment and control groups varies over time) like the standard DID Model. By applying ESA (Event Study Approach) to DID, the hypothesis of parallel trends (no significant difference before the policy is implemented) can be tested more precisely using regression analysis (Beck et al.,2010; Liu et al.,2022). This also

shows the dynamic effects of the policy before and after implementation. The regression equations are shown below.

$$\begin{aligned} \text{Good_Mental_Health}_{it} = & \beta_0 + \beta_1 D_{it}^{-3} + \beta_2 D_{it}^{-2} + \beta_3 D_{it}^{-1} + \beta_4 D_{it}^1 + \beta_5 D_{it}^2 + \beta_6 D_{it}^3 + \\ & \beta_7 X_{it} + v_i + \rho_t + \varepsilon_{it} \end{aligned} \quad (2-5)$$

D_{it}^{-i} : A dummy variable with the value 1 representing the respondent i periods prior to URRMI participation and the value 0 otherwise.

D_{it}^i : A dummy variable with the value 1 indicating the respondent i periods after URRMI participation and 0 otherwise.

X_{it} denotes all control variables, which are the same as the first Model, including $Gender_i$, Age_{it} , $Chronics_{it}$, $night_sleep_{it}$, $IADLs$, $ADLs$, $Married_{it}$, $Income_{it}$, $Work_{it}$, $Primary_{it}$, $Secondary_{it}$, $college_{it}$

2.5.2.2 Placebo Test (robust test)

The placebo test is now being used as a robustness analysis for DID model in an increasing number of papers.¹³ The test's basic idea is to regress with a "fake" policy occurrence time or a "fake" treatment group. To generate a "fake" treatment group, we

¹³ Ye (2022) conducts the Placebo test to prove the robustness of the DID model. This test involves completely random substitution of non-experimental individuals for experimental groups, demonstrating the irreplaceable effect of the Ecological Red Lines (ERL) policy implementation on health promotion. Li et al. (2018) employ the PSM-DID to investigate the impact of the Pollution Information Transparency Index (PITI) list on the Chinese urban environment. The authors also employ a placebo test to show that the PITI abatement effect began in 2018. The placebo test assumes the policy was in effect from 2003 to 2007, but the results show no reductions in emissions from 2003 to 2007.

randomly select the same number of subsamples from all samples as the real treatment group (truly participated in URRMI) and then allocate each subsample a random year of participation in the URRMI. This procedure is then repeated 500 times, and the p-values and regression coefficients for the 500 regressions are calculated. The equation for the regression is as follows.

$$Good_Mental_Health_{it} = \beta_0 + \beta_1 Fake_Treat_{it} + \beta_2 X_{it} + v_i + \rho_t + \varepsilon_{it} \quad (2-6)$$

We can see that compared to Equation (2-4), the only difference in Equation (2-6) is that $Treat_{it}$ is replaced by $Fake_Treat_{it}$. $Fake_Treat_{it}$ is a dummy variable with the value 1 for the "fake" treatment group (the identical number of randomly selected samples as the actual treatment group) and 0 otherwise. If β_1 with the "fake" treatment group remains significant, this indicates that the results of Equation (2-4) are unreliable and that the improvement in mental health could be due to other factors. If the regression results (500 times of β_1) are mostly insignificant, and the regression coefficients are mostly different from the true regression coefficient (α_1 of equation (2-4)), it indicates that our baseline DID Model's regression results are reliable.

2.6 Data and Descriptive Statistics

2.6.1 Data

Our research utilizes the CHARLS (China Health and Retirement Longitudinal Study) database. The CHARLS database is widely employed in ageing and health research (Strauss et al., 2010; Lei et al., 2015).

We utilize the data from the 2011, 2013, 2015, and 2018 waves of the CHARLS. We append the four waves to a total of 75,598 observations. In our study, we focus on middle-aged and older populations. Therefore, we exclude participants younger than 45 years from the CHARLS dataset. This results in the elimination of 250 observations of individuals under 45. The panel data are then adjusted based on the CPI (Consumer Price Index) data obtained from the National Bureau of Statistics of China. Finally, the Winsor method was used to handle the outlier (smoothing the data by shrinking the tails). There are missing values for some variables, so the final number of observations in our two-way fixed effect regression process is 57,915. The flow of data processing is illustrated in Figure 2.6.

Table 2.1 provides the definition of all variables used in the study. Our dependent variable, good mental health, is a dummy variable, with 1 representing good mental health and 0 representing poor mental health. We use the CESD-10 score to measure mental health, with details of the construction method available in Section 2.5.1 Baseline Model, and specific survey questions listed in the Appendix.

2.6.2 Descriptive Statistic

Table 2.2 presents descriptive statistics. We can see that 52.9% of respondents show good mental health. The mean age is 60. We can see that the NRCMI accounts for 74.1% of the total. Nonetheless, the total URRMI is less than 5%. This is because the merger of NRCMI and URBMI into URRMI accelerated only after the State Council's announcement of the integration of the urban and rural residents' basic medical insurance systems in 2016. From 2015 to 2018, as shown in Figure 2.9 below, the NRCMI decreased by six

percentage points to 65.0%, while the URRMI increased by nearly ten percentage points to 12.3%. Due to the fact that these are the total descriptive statistics of the panel data for all four waves, the percentage of URRMI is below 5%. From a dynamic standpoint, however, the increase in URRMI is still evident.

Figure 2.7 shows data descriptions of different types of health insurance. We can see that NRCMI has the greatest mean value of 0.741. Based on our sample, the 2015 NRCMI participation rate was 71%. This participation rate is marginally higher than what the China Health and Family Planning Commission reported. According to Statistical Bulletin on the Development of Health and Family Planning in China (2016), the number of people participating in the NRCMI in China as of 2015 was 670 million, or approximately 48.44% of the population in that year. One reason for the higher percentage of NRCMI in our sample is that 61.3% of our sample is based in rural areas.

As shown in Figure 2.8, NRCMI ranks highest among cities, followed by UEBMI, URBMI, and then private health insurance. According to our data, 89.5% of rural respondents have NRCMI, while 49.72% of urbanites also have NRCMI. Theoretically, the urban population should have UEBMI or URBMI, while rural residents should have NRCMI. Yet, according to our data, 95.47% of the rural population has an agricultural hukou, while 51.15% of the urban population also has an agricultural hukou, which results in this segment of the population being covered by the NRCMI. This could be due to the accelerated urbanization of China, which has led to a large population shift from rural to urban areas. Most of them are migrant workers. Chan (2009) also argues that numerous urban residents have agricultural hukou and that these individuals are rural migrant

workers or dependents. According to the 2021 National Bureau of Statistics of China's Migrant Workers Monitoring Survey, there are 292.51 million migrant workers in 2021, with 133.09 million migrant workers living in the urban area. Chen et al. (2022) also investigate migrant workers' health insurance coverage in China, discovering that only 21.15% of migrant workers participate in UEBMI, while the majority of migrant workers participate in NRCMI.

In addition, Figure 2.8 also shows that in rural areas, 1.04 percent of the population is covered by URBMI and 3.00 percent is covered by UEBMI. This may be a result of the tendency for de-urbanization, in which some people leave the city to enjoy a rural lifestyle. It may be a result of the high population density of cities with expensive real estate, and environmental pollution¹⁴.

Figure 2.9 shows the trend of integrating URBMI and NRCMI into URRMI (Urban and Rural Resident Medical Insurance). We can see that the mean values of NRCMI and URBMI are decreasing, while the mean value of URRMI is increasing, which is due to the fact that URBMI and NRCMI will gradually merge into URRMI. It is interesting to note that from 2015 to 2018, the percentage of respondents with URRMI increased from 2.83% to 12.3%, whilst the NRCMI decreased from 71% to 65% and the URBMI decreased from

¹⁴ Chai et al.(2022) discover a significant negative impact of climate change-induced temperature increases on the urbanisation of China's population by analysing panel data for 28 provinces from 2006 to 2018.

Guan et al.(2018) also argue that the ecological systems of cities, as well as their air and water, have suffered significant damage as a result of urbanization.

Cao et al. (2015) also argue that It is more difficult for city dwellers to enjoy life. This is because living in cities has become more crowded and expensive.

5.9% to 4.1%. This is due to the government's document in 2016, which aims to accelerate the integration of NRCMI and URBMI into URRMI (State Council, 2016) .

2.7. Results

2.7.1 Baseline Model

2.7.1.1 Comparing the mental health effects of UEBMI, URBMI, NRCMI, and Private Health Insurance

Table 2.3 reports the regression results for Equation (2-1), aiming to explore the effect of health insurance on mental health. The dependent variable is good mental health. Column 1 of Table 2.3 shows the regression coefficients for the fixed-effect linear probability model. Column 2 of Table 2.3 shows the marginal effect of our robust model (CRE probit model).

We use a linear probability model with a fixed effect to test the first and second hypotheses. According to the results reported in column 1 of Table 2.3, the coefficient associated with UEBMI is statistically significant and equal to 0.082, which means that having UEBMI is associated with an 8.2 percentage point higher probability of having good mental health. The coefficient of URBMI is statistically significant and equal to 0.034, which suggests that having URBMI is linked to a 3.4 percentage point higher likelihood of being in good mental health. This finding implies that both UEBMI and URBMI have a positive relationship with good mental health, with UEBMI having a

stronger and greater impact than URBMI. In contrast, Table 2.3 reveals that neither NRCMI nor private health insurance coefficients are statistically significant.

The results are partially in line with our first hypotheses, as only UEBMI and URBMI have a positive relationship with good mental health, whereas NRCMI and private health insurance have no association with mental health. Our regression results are also consistent with our second hypothesis, as UEBMI has the greatest impact on mental health compared with other health insurance. Our results are also partially in line with one paper that looks at how UEBMI, URBMI, and NRCMI affect mental health. Liu et al. (2016) use data from the National Survey of Aged Population in Urban/Rural China from 2006 and 2010, finding that UEBMI plays the most important role in mental health, followed by NRCMI and URBMI. Our results differ from those of NRCMI because we investigate different time periods. We utilize data from 2011 to 2018, whereas they utilize data from 2006 to 2010. Between 2011 and 2018, China became more urbanised as an increasing number of migrant workers with NRCMI flocked to the cities. And NRCMI is difficult to use in cities, as reimbursement in township hospitals is greater than in city hospitals, and off-site reimbursement is a challenge. Consequently, our findings from 2011–2018 indicate that NRCMI does not significantly affect mental health. In addition, using the first three waves of the CHARLS, Ma and Oshio (2020) also find that there is no association between NRCMI and mental health. This may be due to the shortcomings of NRCMI, such as slightly lower reimbursement rates, inconvenient reimbursement methods, and low level of coverage of quality medical resources (Ma and Oshio,2020).

The coefficient associated with private health insurance in column 1 is not significant. However, the coefficient associated with private health insurance is positive and statistically significant in column 2. It suggests that having private health insurance may be associated with a 2.4 percentage point higher probability of having good mental health. This result is consistent with our hypothesis 1 that private health insurance positively impacts mental health. Using data from the National Health Interview Survey from 2001 to 2010, Ward and Martinez (2014) reveal that private health insurance can significantly reduce psychological distress among US adults.

Column 1 of Table 2.3 also shows that married, work, night sleep, and income all carry positive and significant coefficients. These coefficients suggest that being married is associated with a 9.1 percentage point higher likelihood of having good mental health. Middle-aged and older adults who are currently working also show a 1.5 percentage point higher probability of being in good mental health. Similarly, the number of hours slept at night and income are associated with a higher probability of good mental health. The coefficient for chronic illness indicates that a one-unit increase in the number of chronic illnesses is associated with a 2.3 percentage point lower probability of having good mental health. The signs of these control variables are consistent with our expectations and the literature we mentioned in the specification section. The coefficient associated with *illiterate_{it}* is significant and negative. As for *college_{it}* We predicted its coefficient to be positive, but it turned out to be negative. According to Chevalier and Feinstein (2006), the relationship between education and mental health is

nonlinear, and low to moderate levels of education are more likely than higher education to reduce the risk of depression in adults.

Compared to other traditional determinants of mental health, the coefficients for the association between health insurance and mental health are relatively large, with the absolute values of coefficients for UEBMI and URBMI being greater than those for chronics, income, IADLs, illiterate, work, and night sleep, and smaller only for married, college, and ADLs. This indicates that the effect of health insurance on mental health is crucial and cannot be overlooked.

The correlated random effect Probit model is used as a robustness test. Column 2 of Table 2.3 shows the marginal effect of the correlated random effect Probit model. After comparison, it is discovered that the Probit model with the correlated random effect produced essentially identical findings to the probability model with fixed effects. Both UEBMI and URBMI are significantly associated with access to good mental health, while NRCMI has no significant impact on mental health. The outcomes for the control variables are also quite similar. The only difference is private health insurance. Therefore, in the following subsection, we will investigate further the impact on mental health when public health insurance is accompanied by private health insurance or not.

2.7.1.2 Is Public Insurance More Effective for Mental Health with Private Coverage?

Below, we further compare the effects of having some public health insurance along with private health insurance and having only some public health insurance on the mental health of middle-aged and older adults. Table 2.4 shows the regression results for

Equation (2-2), which examines the mental health effects of public health insurance with or without private health insurance. The dependent variable is good mental health. Column 1 of Table 2.4 shows the regression coefficients for the fixed-effect linear probability model. Column 2 of Table 2.4 shows the marginal effects of the CRE probit model. Column 1 of Table 2.4 reveals that the coefficient associated with UEBMI_private is statistically significant and equal to 0.146, whereas the coefficient for UEBMI_noprivate is only 0.073 ($P < 0.01$). This indicates that UEBMI accompanied by private health insurance is more likely to be associated with good mental health than UEBMI without private health insurance. Similarly, URBMI_private has a coefficient of 0.092 ($P < 0.05$), whereas URBMI_noprivate has a coefficient of 0.029 ($P < 0.1$). This suggests that URBMI combined with private health insurance is more likely to be associated with good mental health than URBMI alone. DeRigne et al. (2009) examine the relationship between health insurance and unmet mental health needs in the US, noting that when public health insurance is accompanied by private health insurance, unmet mental health needs are reduced by 35%. That is why the impact of private health insurance on mental health cannot be ignored. This result is consistent with our hypothesis 1, which states that private health insurance positively impacts mental health. The signs of these control variables are consistent with our expectations and the literature we mentioned in the specification section. The results of control variables are quite similar to the results of the main specification. For example, Table 2.4 and Table 2.3 display positive and statistically significant coefficients for married, working, night sleep, and income, while negative and significant coefficients for chronics, IADLs, ADLs, college, and illiterate.

Column 2 of Table 2.4 presents the marginal effect of the CRE Probit model. A comparison reveals that the results are essentially the same as those from the fixed-effects probability model.

2.7.1.3 Health Insurance Transitions

We next discuss the impact of switching between different types of public health insurance on mental health. Participants in the UEBMI are primarily employed people (including retirees) who live in cities. By contrast, the majority of URBMI's clients are unemployed urban residents, such as students. The NRCMI covers the population living in rural areas. The outcomes of our regressions are presented in Table 2.5 below. Table 2.5 displays the results of the fixed effect LPM regression of Equation (2-3). The dependent variable is good mental health. Column 1 of Table 2.5 represents the effect of the transition from URBMI to UEBMI on mental health. Column 2 of Table 2.5 represents the impact of the transition from UEBMI to URBMI on mental health. Column 3 of Table 2.5 shows the impact of the transition from NRCMI to UEBMI on mental health. Column 4 of Table 2.5 shows the impact of the transition from UEBMI to NRCMI on mental health. Column 5 of Table 2.5 displays the impact of the transition from NRCMI to URBMI on mental health. Column 6 of Table 2.5 displays the impact of the transition from URBMI to NRCMI on mental health.

From Table 2.5, we can observe that four of these six transitions have a significant effect on mental health. From Column 3, the transition from NRCMI to UEBMI has the greatest effect on mental health, which can be associated with a 12.3 percentage point higher probability of having good mental health. According to our second hypothesis, the

UEBMI has a greater effect on mental health than the NRCMI. Therefore, the transition from NRCMI to UEBMI has a beneficial effect on mental health.

From Column 5, the transition from NRCMI to URBMI is also associated with an 8.4 percentage point higher likelihood of being in good mental health. This is consistent with our Hypothesis 2. Our Hypothesis 2 states that URBMI has a more beneficial effect on mental health than NRCMI. Therefore, the transition from the NRCMI to the URBMI positively affects mental health.

From column 1, switching from URBMI to UEBMI is also linked to a 7.4 percentage point higher probability of having good mental health. However, from Column 2, changing from UEBMI to URBMI is associated with a 9.0 percentage point lower likelihood of having good mental health. This is also in line with Hypothesis 2. According to Hypothesis 2, the UEBMI has a greater positive effect on mental health than the URBMI. As a result, shifting from URBMI to UREMI is beneficial to mental health, whereas switching from URBMI to UEBMI has a negative impact on mental health.

Additionally, we continue to utilize the CRE probit model as a robust model to estimate Equation (2-3). Table A2.8 (which can be found in the Appendix) reports the effect of insurance switching on mental health using the CRE probit model. The results are generally consistent with those of the fixed-effects LPM model. In the probit model, the other two insignificant transitions in the LPM are also significant. In column 4 of Table A2.8, for example, we can observe that switching from UEBMI to NRCMI is associated with a 6.6 percentage point lower probability of having good mental health. Changing from URBMI to NRCMI is associated with a 6.1 percentage point lower probability of

having good mental health. This is also consistent with hypothesis 2, which states that UEBMI and URBMI have a greater impact on good mental health than NRCMI.

We mentioned previously that only one paper used CHARLS (2015) to explore the impact of the transition from UEBMI to URBMI and from UEBMI to NRCMI on the mental health of people with chronic conditions (Li and Yuan, 2019). This study reveals that switching from UEBMI to NRCMI is associated with increased psychiatric problems in chronically ill patients. Our results (Column 4 of Table A2.8) of the CRE probit model also show that switching from UEBMI to NRCMI is associated with a low probability of having good mental health. However, this paper demonstrates that the transition from UEBMI to URBMI does not affect mental health, whereas our results in the second column of Table 2.5 and Table A2.8 are significant. The disparity in results could be attributed to the fact that these two studies are carried out on different populations and with different data waves.

Additionally, the control variables are quite similar to those in the main specification. For instance, the coefficients for chronics are all positive, whereas the coefficients for married are all negative.

2.7.2 DID Model

2.7.2.1 DID Model Results

Next, we discuss the estimates of our time-varying DID illustrated in Equation (2-4), which aims to assess the effect of the consolidation of the URBMI and NRCMI schemes into one scheme, the URRMI. The results are reported in Table 2.6. The first column of

Table 2.6 displays the time-varying DID model results, and the second column displays the CRE probit model results for robustness testing. $Treat_{it}$ is a dummy variable equal to 1 if the respondent participates in URRMI, and 0 otherwise. The coefficient associated with $Treat_{it}$ is statistically significant and equal to 0.029. It suggests that after the merger, residents in both urban and rural areas are 2.9 percentage points more likely to have good mental health. In other words, combining urban and rural residents' insurance is positively and significantly associated with having good mental health in middle-aged and elderly individuals. This is consistent with our hypothesis 3. It is also in line with Tan et al. (2019) and Xie et al. (2019) who found that the merger of urban and rural residents' insurance can increase the scope of drug reimbursement and increase the frequency of people's visits to hospitals, which may, in turn, have a positive impact on middle aged and elderly respondents' mental health. The results for the control variables are also highly congruent with the anticipated sign and main specification. Table 2.6 displays positive and statistically significant coefficients for marriage, employment, night sleep, and income, as well as negative and statistically significant coefficients for chronic diseases, IADLs, ADLs, and illiteracy.

The results of the robustness test are shown in the second column of Table 2.6, and we can see that the results in the second column are generally consistent with the results in the first column. The marginal effect for the independent variable $Treat_{it}$ is also statistically significant and equal to 0.030, and the results for the remaining control variables are similar to those in the first column. For example, in both the first and second columns, the coefficient associated with $married_{it}$ is statistically significant and

equal to 0.092, and the coefficient associated with $IADLs_{it}$ is statistically significant and equal to -0.026. This demonstrates the robustness of our DID model.

2.7.2.2 Event Study

Then, we examine the outcome of the event study of time-varying DID illustrated in Equation (2-5). Event study can test whether time-varying DID meets the assumption of parallel trends. In Figure 2.10, the vertical axis represents good mental health. The horizontal axis is the time axis indicating the time before and after the implementation of the policy. In the three periods preceding the policy's implementation, all coefficients ($\beta_1, \beta_2, \beta_3$) of Equation (2-5) are not significant. This indicates that the differences between the treatment group (participate in URRMI) and the control group (still participate in NRCMI or URBMI) before the policy's implementation are not statistically significant. If there is no significant difference in mental health between the control group and the treatment group prior to the implementation of the policy, this proves that the two groups are comparable. Consequently, the premise assumption of parallel trends is met.

From Figure 2.10, we can also see that the coefficients are still not significant after the policy occurs. This could be explained in light of Figure 2.9, which shows that the percentage of respondents with URRMI only started to grow significantly in the 2018 wave of the survey. Figure 2.10 shows that the coefficient indeed becomes positive in that wave. The fact that it remains insignificant could be because the percentage of respondents with URRMI is still quite small.

2.7.2.3 Placebo Test

Finally, we use the Placebo Test as a further robust test for the time-varying DID model.

In the placebo test, we randomly select the same number of observations as the actual treatment group (truly participate in URRMI) to the "fake" treatment group (the identical number of randomly selected samples as the actual treatment group), then randomly match these individuals to the time of the policy's occurrence, and then conduct 500 times of time-varying DID regressions (Equation (2-6)). The distribution of the 500 estimated coefficients (β_1) and their corresponding p-values are depicted in Figure 2.11. The x-axis represents the magnitude of the estimated coefficients (β_1), while the y-axis represents the density values and p-values. From Figure 2.10, we can see the vast majority of points are located above the 0.1 line, indicating that the majority of p-values are greater than 0.1. And the vast majority of coefficient values(β_1) are significantly off from our actual coefficient of 0.029 (α_1 of Equation (2-4)). This indicates that our DID model's results are plausible.

2.8. Conclusion, Significance, and Limitation

This paper discusses the impact of health insurance on mental health. It examines the differences in the effects of different types of public health insurance and private health insurance on the mental health of older adults. In addition, we also investigate the impact of URRMI on mental health.

Studying the impact of various types of health insurance on the mental health of middle-aged and elderly people enables us to quantify the gaps between various forms of health insurance. For example, both UEBMI and URBMI have a positive impact on mental health, with UEBMI having the greatest impact. However, NRCMI does not affect the mental health of middle-aged and older adults. This may be due to the shortcomings of NRCMI, such as slightly lower reimbursement rates, inconvenient reimbursement methods, and low level of coverage of quality medical resources (Ma and Oshio,2020). Secondly, we compare the mental health effects of having only public health insurance with those of having both public and private health insurance. The results show that people with both public (UEBMI, URBMI) and private health insurance are more likely to have good mental health than those with only public health insurance (UEBMI, URBMI). Thirdly, we examine the effect of switching between various types of public insurance on mental health. The results find that switching from NRCMI or URBMI to UEBMI is positively associated with good mental health. The same is observed for switches from NRCMI to URBMI . However, switching from UEBMI to URBMI is not beneficial to achieving good mental health. This confirms that the UEBMI is superior to the URBMI and NRCMI in promoting mental health. To the best of our knowledge, no literature has yet examined the effects of switching between three different types of public insurance on mental health.

Finally, the effects of the combined URRMI on mental health have not previously been discussed in the literature. Our time-varying DID model shows that the URRMI is positively associated with good mental health. We have previously determined that NRCMI has no effect on mental health, whereas UEBMI and URBMI can promote mental

health. Since the vast majority of rural residents are covered by NRCMI, this disparity between urban and rural areas suggests inequity. However, after the merger, the results show that middle-aged and older adults whose insurance types have been combined into the URRMI are more likely to have good mental health. Based on the findings, the policy implications suggest that the government should work to ensure equitable benefits across different types of public health insurance. Ideally, reimbursement policies for all public insurance types should align with those of UEBMI. This alignment would include increasing reimbursement rates, expanding drug coverage, and providing more convenient reimbursement methods. Such adjustments would ensure that all public health insurance programs offer similar levels of support. This, in turn, would positively impact mental health outcomes.

Additionally, the government should promote both public and private health insurance coverage. Encouraging dual coverage would give middle-aged and older adults more comprehensive benefits. This could potentially improve mental health in these age groups. By supporting access to both types of insurance, the government can help address gaps in mental health support that may exist within public insurance alone.

Finally, the merger policy is efficient and beneficial. The policy implication is to accelerate the process of merging URBMI and NRCMI into URRMI to improve the mental health of middle-aged and older adults. The results also highlight the importance of deeper integration of URBMI and NRCMI into a unified URRMI system. Moving forward with this enhanced merger would promote improved mental health for middle-aged and older

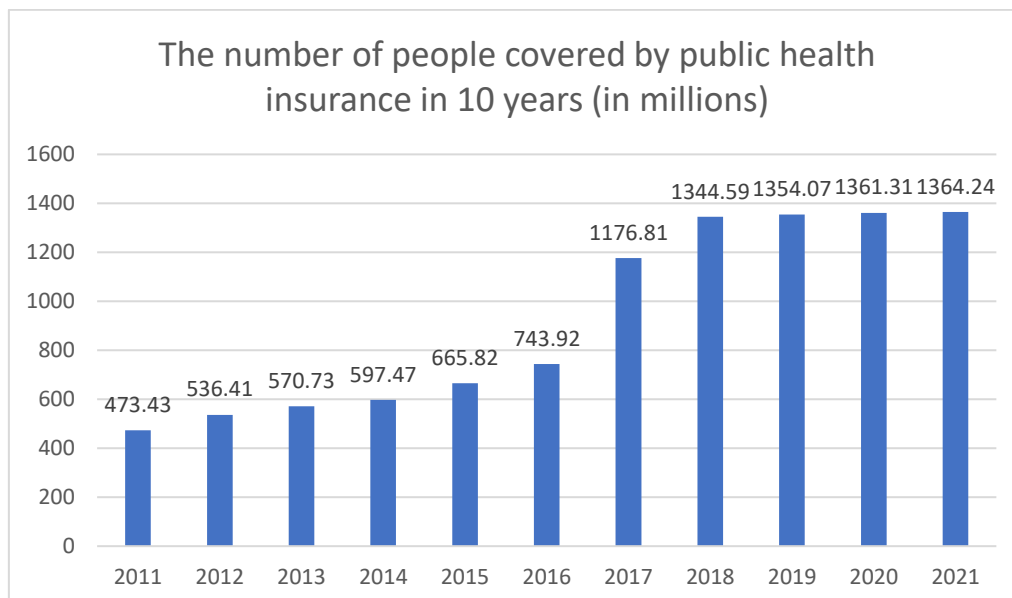
adults. It would also help balance mental health support between urban and rural populations.

Nevertheless, this paper has certain limitations. The measuring of mental health is depended solely on questionnaires completed by respondents. The questionnaire responses may be subjective and inaccurate. Second, we do not have enough waves to properly assess the effects of the URRMI merger.

Future research could examine the effect of other new types of health insurance on the mental health of Chinese seniors, such as, for instance, the new private long-term care insurance health insurance introduced in 2016.

Figures and Tables for Chapter 2

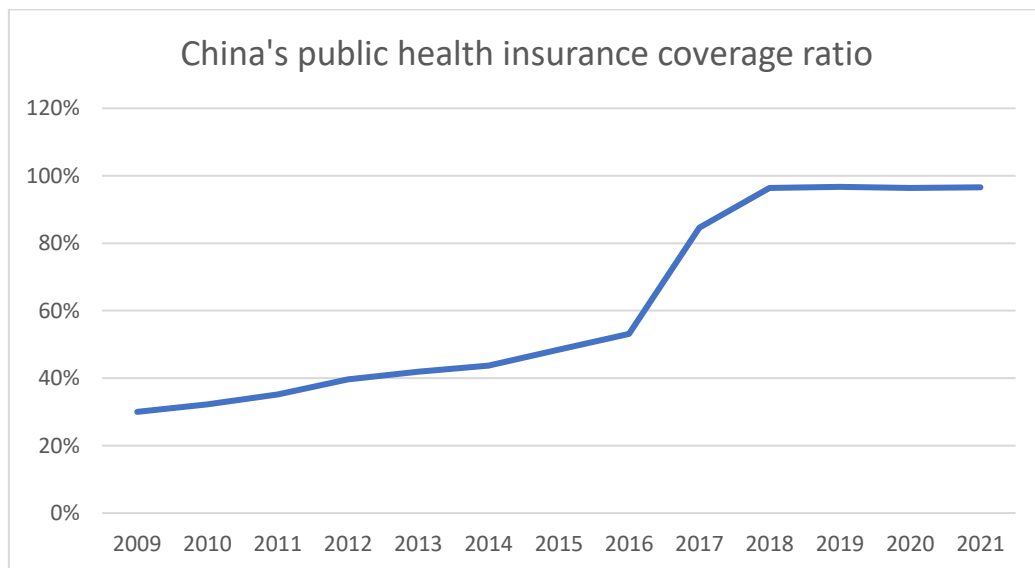
Figure 2.1 Number of People Covered by Public Health Insurance in China (in millions)



Source: Published by C. Textor, 2022

(<https://www.statista.com/statistics/1168852/china-number-of-people-covered-by-different-types-of-social-insurance>)

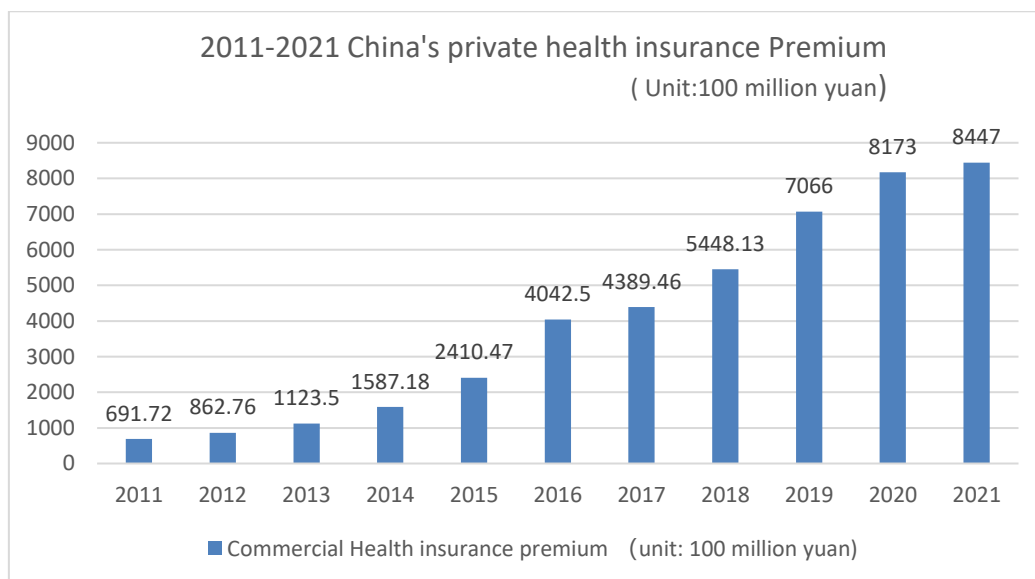
Figure 2.2 China's Public Health Insurance Coverage Ratio



Source: Published by C. Textor, 2022

(https://www.statista.com/topics/1276/population-in-china/#topicHeader_wrapper)

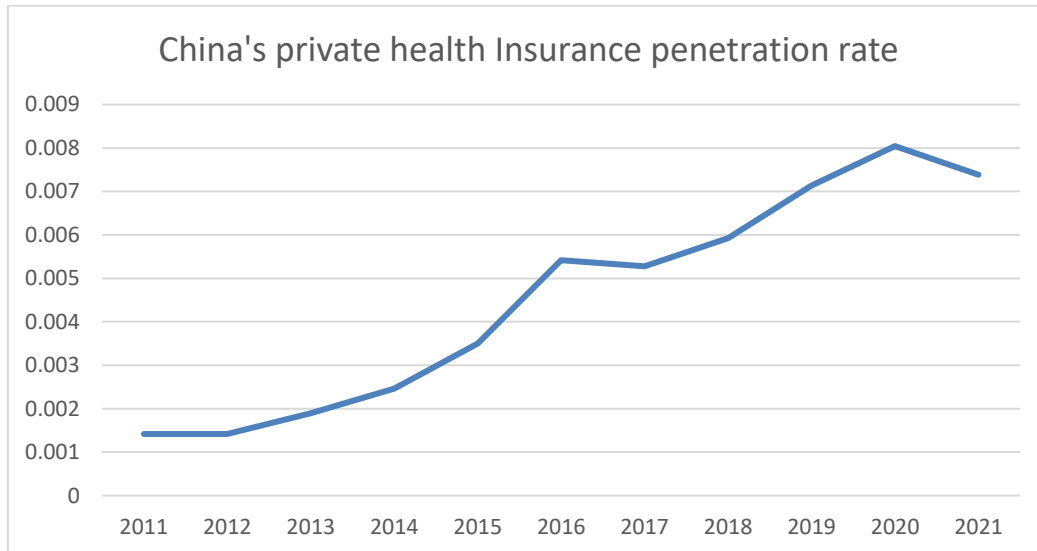
Figure 2.3 2011-2021 China's Private Health Insurance Premium



Source: Published by Daniel Slotta, Mar 16, 2022:

(<https://www.statista.com/statistics/1032552/china-premium-revenue-from-health-insurance/>)

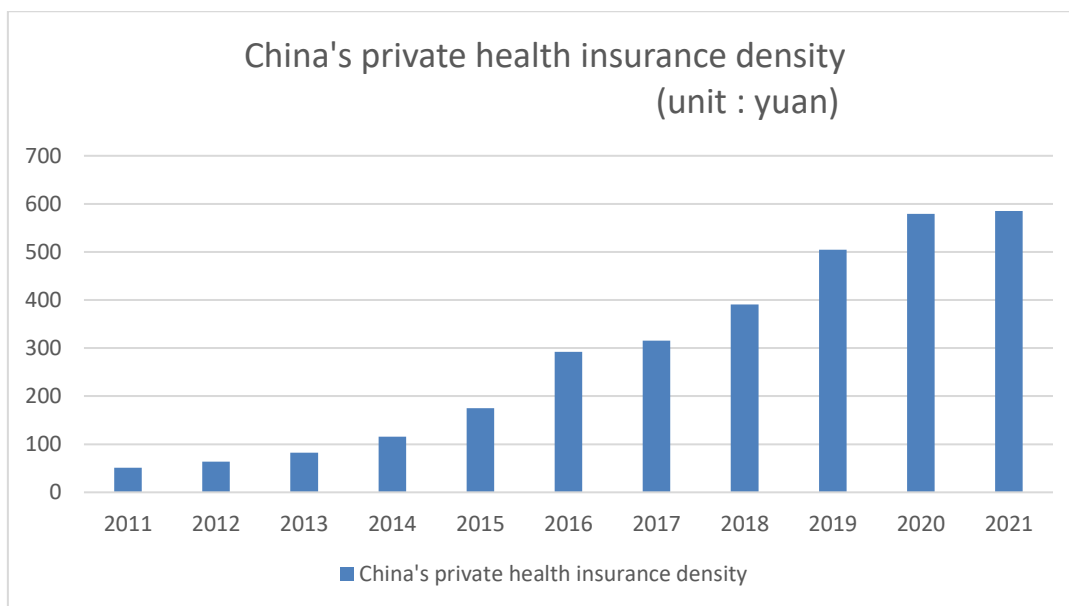
Figure 2.4 2011-2021 China's Private Health Insurance Penetration Rate



(Source: GDP Data from Published by C. Textor, Apr 7, 2021:

<https://www.statista.com/statistics/263770/gross-domestic-product-gdp-of-china/>)

Figure 2.5 2011-2021 China's Private Health Insurance Density



(Population source : <https://www.statista.com/statistics/263765/total-population-of-china/>)

Figure 2.6 Data Processing Flow Chart

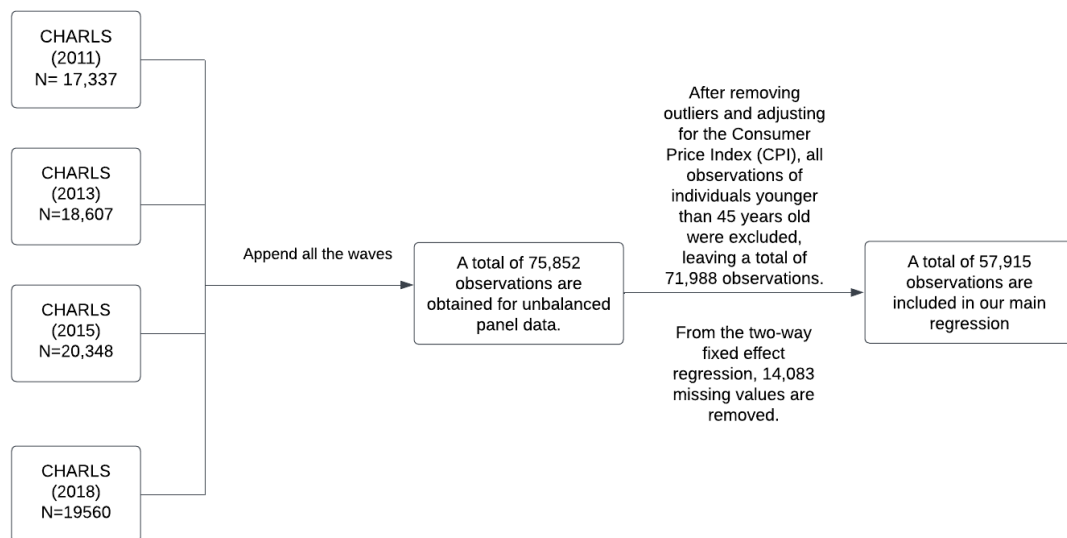


Figure 2.7 Health Insurance Coverage

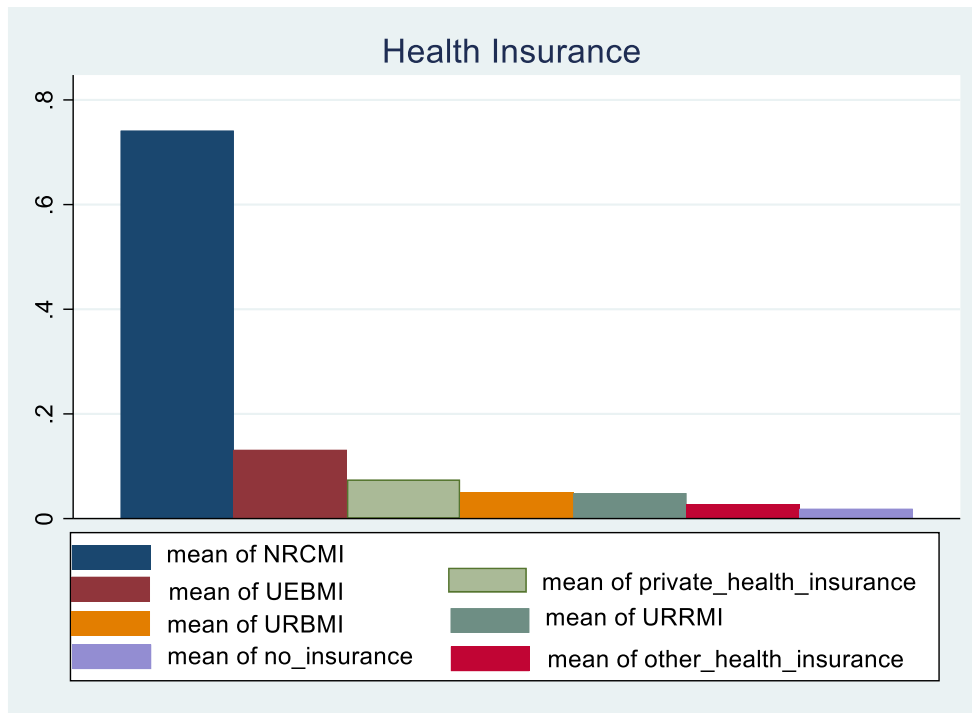


Figure 2.8 Different Types of Health Insurance in Rural and Urban areas

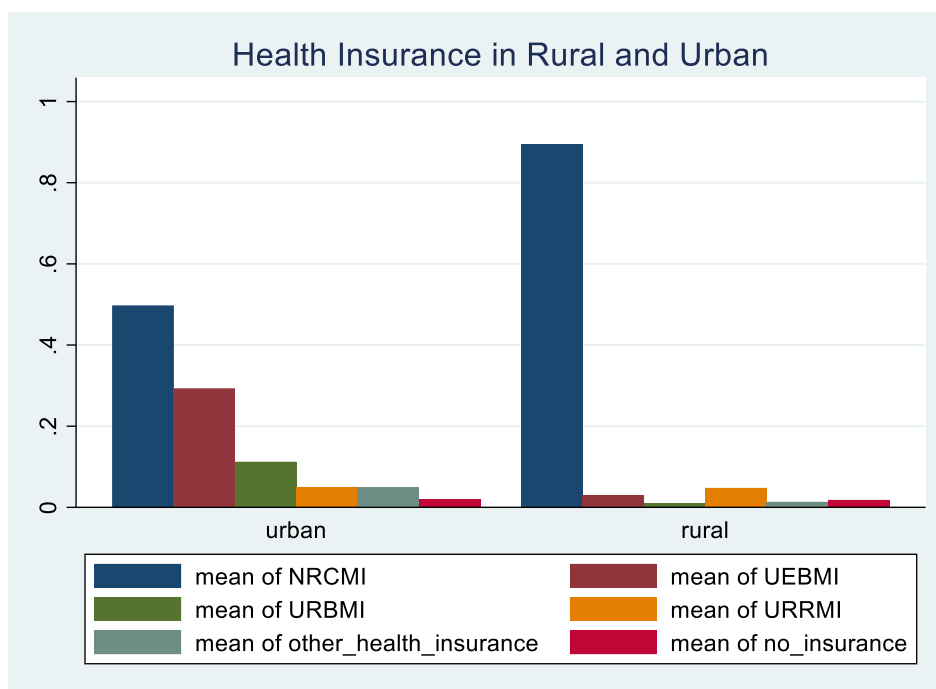


Figure 2.9 Changes in the Mean Value of the Three Types of Public Health Insurance over time

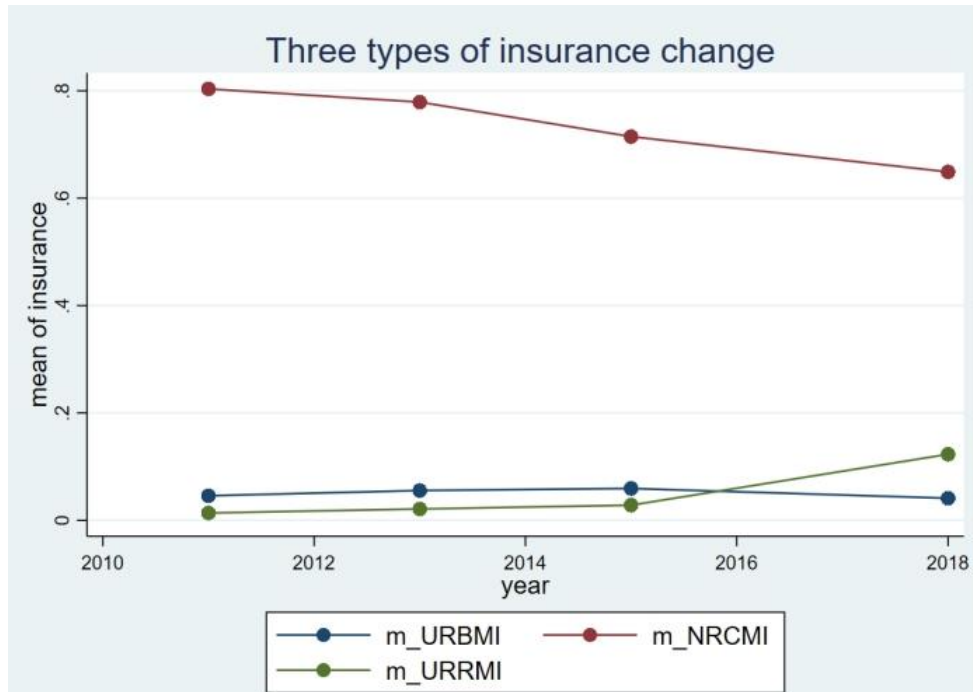


Figure 2.10 Event Study

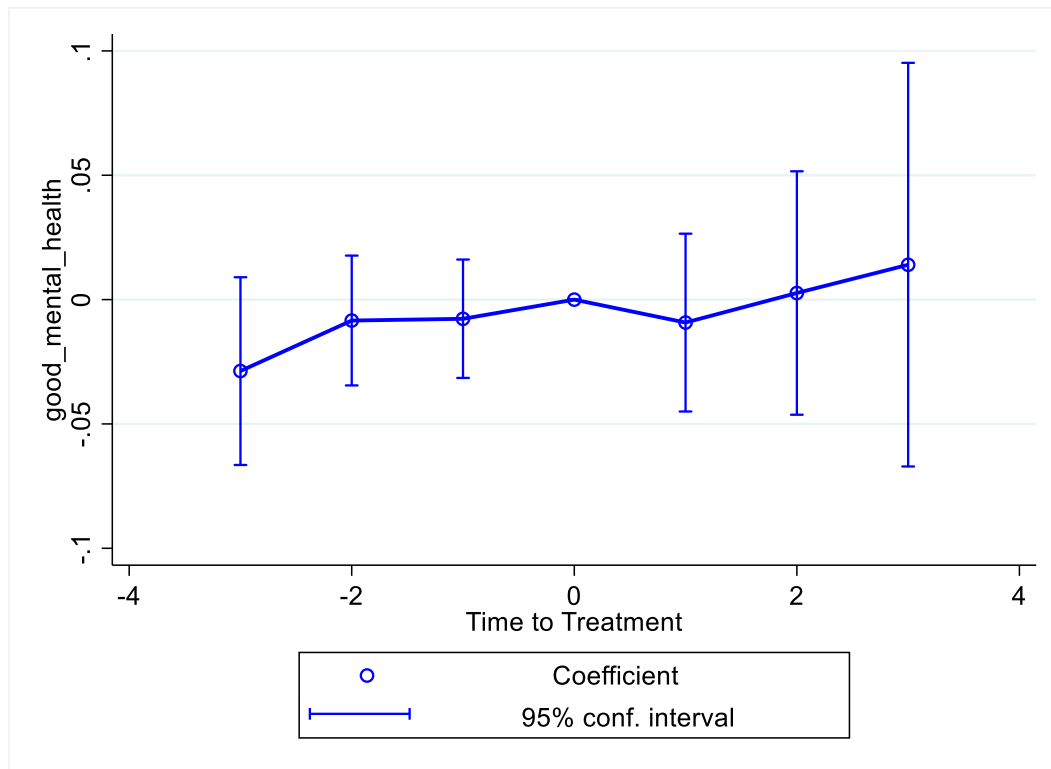
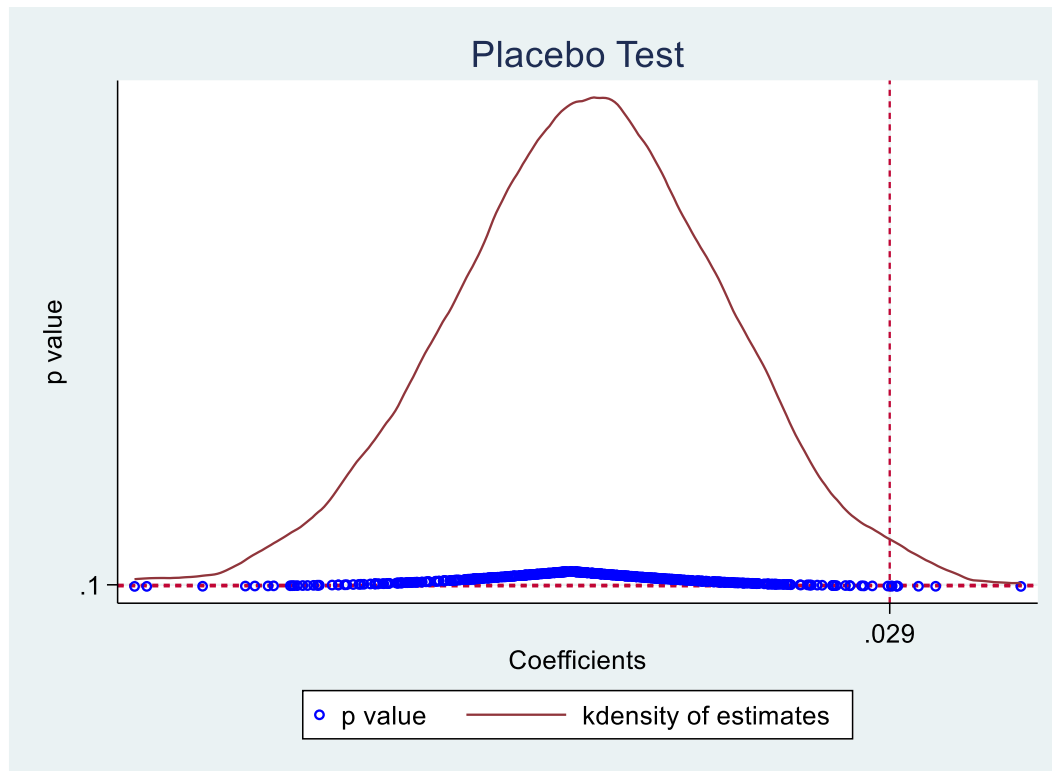


Figure 2.11 Placebo Test



Chapter 2 Tables

Table 2.1 Variables Definitions

VARIABLES	Definition
good_mental_health	Dummy variable with a value of 1 if the respondent has good mental health and 0 otherwise.
Health Insurance	
Private health insurance	Dummy variable with a value of 1 if the respondent is covered by private health insurance, and a value of 0 otherwise.
UEBMI	Dummy variable with a value of 1 if the respondent is covered by Urban Employee Basic Medical Insurance (UEBMI), and a value of 0 otherwise.
URBMI	Dummy variable with a value of 1 if the respondent is covered by Urban Resident Basic Medical Insurance (URBMI), and a value of 0 otherwise.
NRCMI	Dummy variable with a value of 1 if the respondent is covered by New Rural Cooperative Medical Insurance (NRCMI), and a value of 0 otherwise.
URRMI	Dummy variable with a value of 1 if the respondent is covered by Urban and Rural Resident Medical Insurance (URRMI), and a value of 0 otherwise.

UEBMI_private	Dummy variable with a value of 1 if the respondent is covered by both UEBMI and private health insurance, and a value of 0 otherwise.
UEBMI_noprivate	Dummy variable with the value 1 if the respondent has UEBMI but no private health insurance, and the value 0 otherwise.
URBMI_private	Dummy variable with a value of 1 if the respondent is covered by both URBMI and private health insurance, and a value of 0 otherwise.
URBMI_noprivate	Dummy variable with the value 1 if the respondent has URBMI but no private health insurance, and the value 0 otherwise.
NRCMI_private	Dummy variable with a value of 1 if the respondent is covered by both NRCMI and private health insurance, and a value of 0 otherwise.
NRCMI_noprivate	Dummy variable with the value 1 if the respondent has NRCMI but no private health insurance, and the value 0 otherwise.
Trans_URBMI_UEBMI	Dummy variable with a value of 1 if the respondent switch from URBMI to UEBMI, and a value of 0 indicates that the respondent keep URBMI unchanged.
Trans_UEBMI_URBMI	Dummy variable with a value of 1 if the respondent switch from UEBMI to URBMI, and a value of 0 indicates the respondent keep UEBMI unchanged.
Trans_NRCMI_UEBMI	Dummy variable with a value of 1 if the respondent switch from NRCMI to UEBMI, and a value of 0 indicates the respondent keep NRCMI unchanged.
Trans_UEBMI_NRCMI	Dummy variable with a value of 1 if the respondent switch from UEBMI to NRCMI, and a value of 0 indicates the respondent keep UEBMI unchanged.
Trans_NRCMI_URBMI	Dummy variable with a value of 1 if the respondent switch from NRCMI to URBMI, and a value of 0 indicates the respondent keep unchanged.
Trans_URBMI_NRCMI	Dummy variable with a value of 1 if the respondent switch from URBMI to NRCMI, and a value of 0 indicates the respondent keep URBMI unchanged.
Controls	
gender	A dummy variable with a value of 1 if the respondent is male, and 0 if the respondent is female.
age	Age of the individual.
illiterate	Dummy variable equal to 1 if the respondent is illiterate, and zero otherwise.
primary	Dummy variable equal to 1 if the person has completed primary education, and 0 otherwise.
secondary	Dummy variable equal to 1 if the individual has completed secondary school, and 0 otherwise.
college	Dummy variable equal to 1 if the person has earned a college degree, and 0 otherwise.

married	Dummy variable equal to 1 if the respondent is married, and 0 otherwise.
chronics	Number of chronic diseases.
night_sleep	Number of hours slept each night.
ADLs	Number of limitations in basic activities of daily living.
IADLs	Number of limitations in instrumental activities of daily living.
work	Dummy variable equal to 1 if the respondent is now employed, and 0 if the respondent is currently unemployed or retired.
rural	Dummy variable equal to 1 if the respondent lives in the rural area, and 0 if the respondent lives in the urban area.
Income	Average household income of the respondent, including labour income, capital gains, and government transfers.
lincome	Logarithm of the average household income.
year	This variable indicates the survey year.

Table 2.2 Descriptive Statistics

VARIABLES	N	Mean	sd	min	max
good_mental_health	57,323	0.529	0.499	0	1
Health Insurance					
UEBMI	57,323	0.132	0.338	0	1
URBMI	57,323	0.0501	0.218	0	1
NRCMI	57,323	0.741	0.438	0	1
URRMI	57,323	0.0486	0.215	0	1
private_health_insurance	57,323	0.0745	0.263	0	1
Controls					
gender	57,323	0.478	0.500	0	1
age	57,323	60.96	9.637	45	118
illiterate	57,323	0.249	0.432	0	1
primary	57,323	0.559	0.497	0	1
secondary	57,323	0.338	0.473	0	1
college	57,323	0.0224	0.148	0	1
married	57,323	0.870	0.337	0	1
chronics	57,323	1.648	1.603	0	13
night_sleep	57,323	6.267	1.873	1	11
ADLs	57,323	0.367	0.980	0	6
IADLs	57,323	0.447	1.032	0	5
rural	57,915	0.613	0.487	0	1
work	57,323	0.658	0.474	0	1
rural	57,323	0.613	0.487	0	1
year	57,323	2,014	2.606	2,011	2,018
income	57,323	12,457	17,485	0	120,000
lincome	57,323	8.153	2.377	0	11.70

Note: The Chinese Yuan is the income unit of measure.

Table 2.3 Baseline Model Results

VARIABLES	(1) LPM (coefficient)	(2) Probit (Marginal Effect)
UEBMI	0.082*** (5.448)	0.044*** (5.074)
URBMI	0.034** (1.986)	0.029*** (2.689)
NRCMI	-0.008 (-0.763)	-0.005 (-0.730)
private_health_insurance	0.006 (0.621)	0.024*** (3.144)
age	0.001 (0.316)	0.001 (0.387)
chronics	-0.023*** (-7.370)	-0.019*** (-14.242)
married	0.091*** (5.206)	0.090*** (5.118)
gender	-	0.049*** (10.782)
night_sleep	0.008*** (4.639)	0.019*** (17.152)
IADLs	-0.030*** (-7.494)	-0.029*** (-7.350)
ADLs	-0.036*** (-8.715)	-0.036*** (-8.513)
lincome	0.003** (2.272)	0.003** (2.335)
work	0.015* (1.901)	0.016** (2.007)
college	-0.094*** (-2.701)	-0.023* (-1.648)
illiterate	-0.032** (-2.097)	0.010 (1.598)
primary	-0.014 (-0.998)	0.014** (2.181)
Secondary	-0.012 (-0.716)	0.016*** (2.715)
N	57,323	57,323

Note: The table displays the estimates obtained from Equation (2-1). The results of the two-way fixed effect linear probability model are displayed in column 1, while the marginal effects of the CRE probit model are displayed in column 2. The CRE model also includes means of time-varying variables. Their coefficients are not reported for brevity, but are available upon request. N is the

number of observations. Definitions of all variables can be found in Table 2.1. Robust t-statistics are in parentheses. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$

Table 2.4 Differentiating the Effects of Public Insurance Coupled with Private Insurance

VARIABLES	(1) LPM (coefficient)	(2) Probit (Marginal Effect)
UEBMI_private	0.146*** (6.438)	0.108*** (6.763)
UEBMI_noprivate	0.073*** (4.780)	0.034*** (3.772)
URBMI_private	0.092** (2.154)	0.074** (2.245)
URBMI_noprivate	0.029* (1.671)	0.024** (2.198)
NRCMI_private	-0.027 (-1.634)	0.001 (0.117)
NRCMI_noprivate	-0.007 (-0.694)	-0.007 (-0.998)
age	0.001 (0.352)	0.001 (0.411)
chronics	-0.023*** (-7.351)	-0.019*** (-14.192)
married	0.091*** (5.225)	0.090*** (5.141)
gender	-	0.049*** (10.818)
night_sleep	0.008*** (4.665)	0.019*** (17.193)
IADLs	-0.029*** (-7.481)	-0.029*** (-7.337)
ADLs	-0.036*** (-8.718)	-0.036*** (-8.517)
lincome	0.003** (2.235)	0.003** (2.316)
work	0.015* (1.903)	0.016** (2.012)
college	-0.086** (-2.479)	-0.025* (-1.806)
illiterate	-0.033** (-2.133)	0.010 (1.594)

primary	-0.014 (-1.002)	0.014** (2.203)
secondary	-0.012 (-0.720)	0.016*** (2.699)
N	57,323	57,323

Note: The table reports estimates obtained from Equation (2-2). Column 1 reports estimates obtained using the linear probability fixed effects model, while the marginal effects of the CRE probit model are displayed in column 2. The CRE model also includes means of time-varying variables. Their coefficients are not reported for brevity, but are available upon request. N is the number of observations. Definitions of all variables can be found in Table 2.1. Robust t-statistics are in parentheses. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

Table 2.5 Insurance Transition

VARIABLES	(1) all	(2) all	(3) all	(4) all	(5) all	(6) all
Trans_URBMI_UEBMI	0.074** (1.996)					
Trans_UEBMI_URBMI		-0.090*** (-2.604)				
Trans_NRCMI_UEBMI			0.123*** (3.947)			
Trans_UEBMI_NRCMI				0.005 (0.102)		
Trans_NRCMI_URBMI					0.084** (2.545)	
Trans_URBMI_NRCMI						-0.063 (-1.578)
age	0.005 (0.339)	-0.013 (-1.209)	0.001 (0.384)	-0.013 (-1.259)	0.001 (0.370)	0.001 (0.079)
chronics	-0.035* (-1.821)	-0.011 (-1.142)	-0.019*** (-4.736)	-0.008 (-0.824)	-0.019*** (-4.890)	-0.037** (-1.965)
married	0.124 (1.568)	0.110** (2.028)	0.096*** (4.258)	0.091 (1.581)	0.096*** (4.261)	0.179** (2.183)
o.gender	-	-	-	-	-	-
night_sleep	-0.007 (-0.664)	0.012 (1.622)	0.010*** (4.557)	0.015** (2.017)	0.010*** (4.552)	-0.001 (-0.109)
IADLs	0.002	-0.067***	-0.025***	-0.064***	-0.026***	0.014

	(0.062)	(-3.738)	(-5.410)	(-3.526)	(-5.496)	(0.620)
ADLs	-0.060**	-0.046**	-0.031***	-0.044**	-0.030***	-0.077***
	(-2.376)	(-2.324)	(-6.471)	(-2.278)	(-6.361)	(-3.247)
lincome	-0.010*	0.002	0.002	0.004	0.002	-0.010
	(-1.651)	(0.428)	(1.158)	(0.850)	(1.163)	(-1.581)
work	0.120***	-0.023	0.014	-0.029	0.014	0.099**
	(2.753)	(-0.893)	(1.376)	(-1.143)	(1.452)	(2.501)
college	0.056	-0.113***	0.086	-0.118***	0.113	0.123
	(0.431)	(-2.696)	(0.803)	(-2.760)	(0.964)	(0.668)
illiterate	-0.060	-0.100	-0.038**	-0.077	-0.037**	0.011
	(-0.522)	(-1.265)	(-2.093)	(-1.006)	(-2.043)	(0.133)
primary	0.064	-0.067	-0.019	-0.070	-0.018	0.141*
	(0.762)	(-1.047)	(-1.155)	(-1.165)	(-1.099)	(1.680)
secondary	-0.068	-0.033	0.012	-0.037	0.011	-0.163*
	(-0.857)	(-0.600)	(0.595)	(-0.671)	(0.530)	(-1.849)
N	2,330	6,125	39,262	6,093	39,220	2,203

Note: The table reports estimates obtained from Equation (2.3) using the linear probability fixed effects model. Definitions of all variables can be found in Table 2.1. According to the definition of these variables (Trans_NRCMI_URBMI, Trans_UEBMI_NRCMI, Trans_URBMI_UEBMI, Trans_UEBMI_NRCMI, Trans_UEBMI_URBMI, Trans_NRCMI_URBMI, and Trans_NRCMI_UEBMI), we know that the number of these variables varies (descriptive statistics of these variables can be found in Appendix Table A2.7), as a result, the number of regressions in the six columns is not the same. Robust t-statistics are in parentheses. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$. N is the number of observations.

Table 2.6 Results of Time-varying DID model

VARIABLES	(1) DID (coefficient)	(2) Probit (Marginal Effect)
Treat	0.029** (2.135)	0.030*** (3.226)
age	0.003 (1.128)	0.003 (1.188)
chronics	-0.025*** (-7.313)	-0.018*** (-11.589)
married	0.092***	0.092***

	(4.821)	(4.750)
gender	-	0.050***
		(9.598)
night_sleep	0.010***	0.020***
	(5.100)	(15.898)
IADLs	-0.026***	-0.026***
	(-6.198)	(-6.189)
ADLs	-0.033***	-0.035***
	(-7.671)	(-7.597)
lincome	0.002*	0.002*
	(1.678)	(1.675)
work	0.020**	0.021**
	(2.276)	(2.395)
college	0.007	-0.070
	(0.073)	(-1.494)
illiterate	-0.031**	0.007
	(-1.979)	(1.062)
primary	-0.013	0.008
	(-0.911)	(1.231)
secondary	-0.004	0.025***
	(-0.208)	(3.762)
N	44,207	44,207

Note: The table reports estimates obtained from Equation (2-4). Column 1 reports coefficients obtained using the DID model, while the marginal effects of the CRE probit model are displayed in column 2. The CRE model also includes means of time-varying variables. Their coefficients are not reported for brevity, but are available upon request. N is the number of observations. Definitions of all variables can be found in Table 2.1. Robust t-statistics are in parentheses. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

Appendix for Chapter 2

Figure A2.12 The CES-D 10 form

	Rarely or none of the time (less than 1 day)	Some or a little of the time (1-2 days)	Occasionally or a moderate amount of time (3-4 days)	All of the time (5-7 days)
1. I was bothered by things that usually don't bother me.	☐	☐	☐	☐
2. I had trouble keeping my mind on what I was doing.	☐	☐	☐	☐
3. I felt depressed.	☐	☐	☐	☐
4. I felt that everything I did was an effort.	☐	☐	☐	☐
5. I felt hopeful about the future.	☐	☐	☐	☐
6. I felt fearful.	☐	☐	☐	☐
7. My sleep was restless.	☐	☐	☐	☐
8. I was happy.	☐	☐	☐	☐
9. I felt lonely.	☐	☐	☐	☐
10. I could not "get going."	☐	☐	☐	☐

Source: CHARLS Database Handbook

Table A2.7 Descriptive Statistics of Insurance Transitions Variables

VARIABLES	N	Mean	sd	min	max
Trans_URBMI_UEBMI	2,345	0.1678	0.374	0	1
Trans_UEBMI_URBMI	6,125	0.4882	0.216	0	1
Trans_NRCMI_UEBMI	39,262	0.0115	0.107	0	1
Trans_UEBMI_NRCMI	6,093	0.373	0.189	0	1
Trans_NRCMI_URBMI	39,220	0.0087	0.093	0	1
Trans_URBMI_NRCMI	2,203	0.1394	0.3464	0	1

Table A2.8 Insurance Transition (CRE probit)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	all	all	all	all	all	all

Trans_URBMI_UEBMI 0.025

	(0.889)					
Trans_UEBMI_URBMI	-0.053**					
	(-2.101)					
Trans_NRCMI_UEBMI		0.096***				
		(4.071)				
Trans_UEBMI_NRCMI			-0.066**			
			(-2.268)			
Trans_NRCMI_URBMI				0.066**		
				(2.475)		
Trans_URBMI_NRCMI					-0.061**	
					(-2.126)	
age	0.010	-0.017*	0.002	-0.014	0.003	0.011
	(0.860)	(-1.807)	(1.026)	(-1.634)	(1.106)	(0.920)
chronics	-0.021***	-0.015***	-0.019***	-0.016***	-0.019***	-0.022***
	(-3.507)	(-4.113)	(-11.348)	(-4.346)	(-11.337)	(-3.509)
married	0.081	0.115**	0.092***	0.101**	0.092***	0.172**
	(1.159)	(2.419)	(4.433)	(2.046)	(4.413)	(2.277)
gender	0.057***	0.022	0.056***	0.023*	0.055***	0.077***
	(2.589)	(1.642)	(10.094)	(1.658)	(9.917)	(3.374)
night_sleep	0.016***	0.022***	0.020***	0.022***	0.020***	0.019***
	(2.716)	(5.691)	(15.149)	(5.718)	(15.264)	(3.068)
IADLs	-0.007	-0.055***	-0.028***	-0.056***	-0.028***	-0.014
	(-0.341)	(-3.688)	(-6.368)	(-3.764)	(-6.377)	(-0.682)
ADLs	-0.053**	-0.044***	-0.031***	-0.042***	-0.031***	-0.060***
	(-2.325)	(-2.721)	(-6.687)	(-2.588)	(-6.653)	(-2.767)
lincome	-0.006	0.004	0.001	0.003	0.001	-0.007
	(-1.033)	(0.878)	(0.856)	(0.784)	(0.849)	(-1.182)
work	0.082**	-0.027	0.014	-0.025	0.015	0.060*
	(2.136)	(-1.158)	(1.551)	(-1.077)	(1.609)	(1.679)
college	0.013	-0.002	-0.070	-0.006	-0.042	-0.041

	(0.236)	(-0.133)	(-1.171)	(-0.327)	(-0.692)	(-0.516)
illiterate	-0.003	-0.039	0.010	-0.067*	0.009	-0.003
	(-0.066)	(-1.050)	(1.362)	(-1.863)	(1.260)	(-0.083)
primary	-0.008	-0.009	0.010	-0.015	0.009	0.004
	(-0.239)	(-0.335)	(1.411)	(-0.604)	(1.220)	(0.106)
secondary	0.012	0.004	0.026***	0.012	0.025***	0.049*
	(0.415)	(0.212)	(3.666)	(0.660)	(3.596)	(1.727)
N	2,330	6,125	39,262	6,093	39,220	2,203

Note: The table reports estimates obtained from Equation (2-3) using the CRE Probit model. The CRE model also includes means of time-varying variables. Their coefficients are not reported for brevity, but are available upon request. N is the number of observations. Definitions of all variables can be found in Table 2.1. According to the definition of these variables (Trans_NRCMI_URBMI, Trans_UEBMI_NRCMI, Trans_UEBMI_URBMI, Trans_UEBMI_NRCMI, Trans_UEBMI_URBMI, Trans_NRCMI_URBMI, and Trans_NRCMI_UEBMI) , we know that the number of these variables varies, which explains why the number of regressions in the six columns is not the same. Robust t-statistics are in parentheses. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

Chapter 3 Impact of Health Insurance on Child Healthcare Utilization in China

3.1 Introduction

This study is the first to investigate the extent to which health insurance coverage affects children's healthcare utilization in the context of China. Understanding this relationship in China is important because it can help us evaluate whether the current health insurance effectively promotes healthcare access for children. We conduct our investigation by focusing on the differences in the effects of public versus private health insurance in China. We believe that China is an ideal laboratory for this research question for the following two reasons. First, while health insurance coverage is widespread among adults in China, the coverage rates for children are relatively lower: Li and Fang (2018) document in fact that, over the period 2010-2014, only about 70% of children were enrolled in any health insurance plan. This is further supported by Xiong et al. (2013), who report that just 62.2% of children under five have health insurance coverage in cities like Suzhou, Wuhan, and Guiyang in 2010.

In China, public health insurance for children primarily includes the Urban Resident Basic Medical Insurance (URBMI) and the New Rural Cooperative Medical Insurance (NRCMI). These programs have been gradually integrated into the Unified Urban and Rural Resident Medical Insurance (URRMI) to streamline services and improve coverage. One reason for children's low health insurance enrolment rate is that these schemes are voluntary, unlike the compulsory Urban Employee Basic Medical Insurance (UEBMI) for adults. Moreover, the current health insurance policy is heavily focused on

hospitalization reimbursements with less emphasis on outpatient services¹⁵, which does not fully align with children's healthcare needs that predominantly involve outpatient care for non-serious conditions. This discrepancy often results in high out-of-pocket medical expenses for families, reducing the attractiveness of the insurance for children's healthcare needs.

Second, although the penetration of private health insurance in China is not high, many commercial insurance companies have introduced health insurance products specifically designed for children under 18¹⁶. These private insurance companies usually offer high-end medical services and faster medical processing options. This differentiated insurance service better meets the needs of children for high-quality medical care, providing more comprehensive health protection for children and indicating potential market and policy optimization opportunities to improve health insurance schemes for children.

Our analysis, which is based on data from the 2010 to 2020 waves of the China Family Panel Studies (CFPS), reveals several key findings. Firstly, children with health insurance demonstrate higher healthcare utilization rates than those without insurance. This

¹⁵ According to the National Healthcare Security Administration (2019), the outpatient reimbursement rate for the New Rural Cooperative Medical Insurance (NRCMI) is 35%-50%, with a cap of approximately 3,000 yuan. Hospitalization reimbursement rates range from 55% to 75%, with a maximum limit of approximately 180,000 yuan. Under the Urban Resident Basic Medical Insurance (URBMI), the outpatient reimbursement rate is approximately 50%, with a 2,000 yuan cap. The reimbursement rate for hospitalization is approximately 70%, with a maximum limit of around 170,000 yuan.

¹⁶ For example, in 2021, Ping An Insurance Company of China launched the Ping An Children's Medical Insurance E plan. This plan covers children from 30 days after birth up to 18 years old. It includes vaccines for children, coverage for common childhood diseases, and exclusive family doctor services. For more details, please visit the following link :https://baoxian.pingan.com/pa18shopnst/nstShop/index.html#/productInfo/ZP020501?WT.mc_id=T00-WT-PAHOME-baoxian-jiankangxian-all

suggests that health insurance effectively enhances healthcare utilization among children in China. Secondly, children covered by public health insurance exhibit higher healthcare service utilization rates than those covered by private health insurance, making it crucial to promote participation in public health insurance programs. Thirdly, the integration of Urban Resident Basic Medical Insurance (URBMI) and New Rural Cooperative Medical Insurance (NRCMI) into the unified Urban and Rural Resident Medical Insurance (URRMI) is associated with increased healthcare utilization rates among children, making it crucial to deepen the implementation of the URRMI policy across all cities in China.

Our paper contributes to the literature which looked at the effects of health insurance on healthcare utilization among the adult Chinese population (e.g., Zhou et al., 2020; Lee et al., 2022), by focusing, for the first time, on children. This focus is crucial, given the distinct healthcare needs of children compared to adults. Although some studies have explored children's healthcare utilization in the U.S. (e.g., Lave et al., 1998; Cassedy et al., 2008; Kreider et al., 2016), there is no research in China. Given the unique characteristics of China's health insurance system, it is essential to study this topic within the Chinese context. In China, children are less likely to be covered by public insurance compared to adults. Unlike countries like the United States, which have specific public insurance programs for children, China does not offer a dedicated health insurance scheme solely for children. This difference underscores the necessity and novelty of research on children's healthcare utilization in China.

Secondly, we contribute to the literature on the effects of URRMI, a staged pilot policy. Most of the existing studies have focused on the effects of URRMI on healthcare utilization among middle-aged and older adults, treating the policy as a uniform policy (e.g., Su et al., 2019; Zhang et al., 2023; Fan et al., 2021). We are the first study to investigate the impact of URRMI on children's healthcare utilization. Additionally, we use a time-varying Difference-in-Differences (DID) approach to account for the different implementation timelines across provinces. This method allows us to better and more accurately capture the dynamic effects of the policy.

The remaining sections of the paper are organized as follows. Section 3.2 introduces the background of public health insurance and private health insurance for Children in China. Section 3.3 presents a thorough overview of the existing literature with a focus on the gaps that our study aims to fill. Section 3.4 explains our hypothesis. Section 3.5 introduces our baseline specifications and estimation methods. Section 6 introduces the data and presents descriptive statistics. Section 3.7 presents and discusses our empirical results. Section 3.8 concludes and discusses the policy implications of our findings, limitations, and directions for further research.

3.2 Background

3.2.1 Public Health Insurance for Children

In China, public health insurance includes Urban Employee Basic Medical Insurance (UEBMI), Urban Resident Basic Medical Insurance (URBMI), and New Rural Cooperative

Medical Insurance (NRCMI). Since UEBMI is designed for employees, children are not covered under this scheme because child labor is illegal in China. As a result, children in urban areas mainly benefit from URBMI, while those in rural regions are covered by NRCMI. According to the National Healthcare Security Administration (2019), UEBMI and NRCMI typically have lower reimbursement rates compared to UEBMI. Both URBMI and NRCMI are voluntary. In most areas, the premiums for URBMI and NRCMI are uniform for both children and adults, although some cities offer subsidies or reduced premiums for newborns and children¹⁷.

Disparities between URBMI and NRCMI led to a pilot program aimed at integrating these insurances into a unified Urban and Rural Resident Medical Insurance (URRMI). The integration of China's urban and rural medical insurance systems was first piloted by Tianjin in 2008 and finished integration by 2009. Subsequently, from 2011 to 2015, provinces including Chongqing, Ningxia, Guangdong, Qinghai, Zhejiang, Shandong, and Fujian successfully completed their mergers. In 2016, the State Council released a document aimed at accelerating the merger of rural and urban medical insurance systems across China. This push resulted in an additional 17 provinces integrating their systems from 2016 to 2018. The final stages of this nationwide integration saw Anhui, Jilin, Shaanxi, and Tibet complete their mergers between 2019 and 2020, with Jilin Province finalizing its process in January 2021, leading to nearly universal coverage

¹⁷ In 2022, Chengdu introduced a medical insurance policy that set lower premiums for children and students compared to adults. This adjustment aims to enhance healthcare affordability for younger demographics (United Nations Children's Fund (UNICEF) China Office, 2023).

across China. This policy has aligned medical insurance coverage between rural and urban residents, promoting equity in healthcare access across different populations.

According to the State Council on the Integration of the Urban and Rural Residents Basic Medical Insurance System (2016), this integration aims to align reimbursement criteria to the highest standards of both insurance schemes. Prior to the merger, the outpatient reimbursement rate under NRCMI ranged from 35% to 50%, while URBMI offered around 50%. Since merging into URRMI, the outpatient reimbursement rate has been standardized at approximately 50%. In addition, after the merger, the number of designated hospitals has increased compared to when they operated independently. According to Li et al. (2023), after the insurance merger, the integration of healthcare administration between urban and rural areas is more streamlined, making it easier for urban and rural residents to transfer and continue their healthcare coverage.

3.2.2 Private Health Insurance for Children

In China, commercial health insurance is known for providing superior service quality and quicker access to medical care, including enhanced coverage for serious illnesses (Wu et al., 2020). China's private insurance market has grown significantly over the last decade. According to the United Nations Children's Fund China Office (2023), health insurance is children's most popular commercial insurance. With increased parental awareness of insurance benefits for children, there is a rising market for health insurance plans customized only for children. These policies often feature benefits such as regular developmental check-ups and dental care, catering specifically to the needs of children.

3.3 Literature Review

3.3.1 Impact of Health Insurance on Healthcare Utilization in China

Zhou et al. (2020) explore the relationship between health insurance and healthcare utilization among the middle-aged and elderly in China. Using the 2011, 2013 and 2015 waves of the China Health and Retirement Longitudinal Study (CHARLS), they explore the impact of the UEBMI, URBMI, NRCMI, and private health insurance schemes on inpatient and outpatient service utilization. They find that individuals with medical insurance generally utilize more healthcare services, with marked differences among the types of insurance. Specifically, those with UEBMI show a significantly higher use of inpatient services compared to individuals covered by NRCMI. However, compared to NRCMI beneficiaries, UEBMI holders show no significant difference in the utilization of outpatient services. This may be because UEBMI offers more generous hospitalization benefits and reimburses at a higher rate compared to the NRCMI. However, there is little difference in the outpatient component. On the other hand, individuals insured by URBMI are less likely to use outpatient services than those with NRCMI, likely due to URBMI not covering these services. The use of inpatient services does not significantly differ between URBMI and NRCMI participants. Furthermore, no significant differences in the use of either outpatient or inpatient services are found for individuals with private health insurance compared to those covered by NRCMI. However, several limitations are inherent in the study's design and methodology. Specifically, the results are obtained using a random effects logistic model, which assumes no correlation between individual traits and the type of health insurance. Yet, if individuals with certain traits disproportionately enroll in a specific insurance type, this could bias the observed effects

of that insurance on healthcare utilization. In addition, the study does not account for the fact that URBMI and NRCMI were merged into URRMI in some provinces during the research period. This oversight could lead to inaccuracies in assessing the individual impacts of URBMI and NRCMI on healthcare utilization.

Lee et al. (2022) explore the relationship between health insurance coverage and access to healthcare among 19,059 middle-aged and elderly people. To this end, they use the 2018 wave of the CHARLS. The paper divides insurance status into four types according to the coverage of medical care costs: high-coverage insurance schemes (including UEBMI and private health insurance), moderate-coverage insurance (including URBMI and URRMI), low-coverage insurance (including NRCMI), and no insurance. Access to care is measured by whether individuals have at least one physical examination, attend a medical office, receive inpatient care, and are satisfied with local medical services. The results show that insured individuals have a significantly higher likelihood of undergoing physical examinations, receiving inpatient treatment, and reporting higher satisfaction with medical services compared to those without health insurance. Furthermore, there is a positive correlation between the extent of coverage and the likelihood of accessing medical services. Specifically, individuals with high-coverage insurance are more likely to have physical exams, visit medical offices, and receive inpatient care compared to those with moderate coverage, and those with moderate coverage are more likely to access medical services than those with low coverage. Although the paper thoroughly compares different types of health insurance, the classification into four types of insurance coverage has limitations. For instance, classifying UEBMI and private health insurance together as high-coverage insurance may not be appropriate, as it is unclear

which type of insurance more significantly affects medical access. Additionally, although the study utilizes four dummy variables to measure access to medical care, it fails to consider the total number of outpatient visits, which would provide a measure of the frequency of hospital visits. Lastly, the study's reliance on a single wave of the CHARLS dataset limits its ability to establish causality. A longitudinal analysis examining the impact of insurance coverage on access over time would provide a more robust understanding.

Zhang et al. (2020) examine the impact of health insurance on healthcare service utilization among migrant workers in China. Utilizing data from the 2008 and 2009 Rural-Urban Migration in China (RUMiC) Project, the authors analyze the influence of various insurance schemes like UEBMI, URBMI, NRCMI, and private insurance on medical service use. The findings reveal that having health insurance significantly increases the probability of migrant workers making use of medical consultations and preventive medical services. Moreover, all types of health insurance except NRCMI are associated with increased medical spending. This may be due to the NRCMS policy asking migrant workers to initially pay for their healthcare expenditure and seek reimbursement later when they return to their hometowns. However, migrant workers' insurance status is usually unstable due to mobility between regions and shifting employment conditions. With changing healthcare policies over the research period, it may have an impact on the accuracy of the findings.

Huang and Liu (2023) examine the impact of early childhood exposure to the New Rural Cooperative Medical Scheme (NRCMS) on adolescent health, cognitive, and educational

outcomes in rural China. The study analyses 13,563 observations from the China Family Panel Studies (CFPS) spanning 2010 to 2016. The authors use a difference-in-differences (DID) approach, leveraging the staggered introduction of the NRCMS across counties aligned with individuals' birth years. The findings reveal significant improvements in the assessed outcomes for those exposed to NRCMS from birth to age five, with no notable benefits from exposure after age five. This is because starting NRCMS before the age of five not only allows for better prevention of childhood illnesses but also helps build a stronger physical foundation. The study also explores mechanisms using data drawn from the China Health and Nutrition Survey (CHNS) from 1997 to 2011, identifying factors like better preventive care, enhanced prenatal care, better birth outcomes, and reduced medical expenditure risks as key mediators. This demonstrates that having health insurance coverage during childhood improves access to healthcare services. However, the study faces limitations. Firstly, this paper does not have specific data on whether individuals participated in the NRCMS during childhood. It can only estimate participation based on when the province or city implemented NRCMS coverage. Due to the non-mandatory nature of the NRCMS and its initially low uptake, especially among children, this makes it difficult to determine individual involvement. This uncertainty makes it difficult to definitively link the presence of NRCMS in a county to actual insurance coverage for children there, potentially weakening the strength of the study's conclusions about the NRCMI's impact. Furthermore, the findings may not apply to urban populations, as the study focuses on rural areas, where healthcare access and utilization patterns may differ substantially. Finally, the findings may be biased due to the reliance on self-reported data for health status and hospitalization.

3.3.1.1 Impact of the Merger of Insurance Schemes on Healthcare Utilization in China

Su et al. (2019) explore the impact of the Urban and Rural Resident Medical Insurance Schemes (URRMI) on the utilization of medical services among middle-aged and elderly people, using data on 13,305 participants taken from the 2011 and 2015 waves of the CHARLS. The outcome variables are need-but-not-outpatient care (NOC) and need-but-not-inpatient care (NIC). NOC/NIC are circumstances in which individuals require outpatient/inpatient medical services, but are unable to access them due to barriers such as cost, convenience, etc. The research focuses on four provinces that started piloting the URRMI between 2011 and 2015 as the treatment group, while provinces that implemented URRMI before 2011 are excluded from the sample. The results show that the URRMI policy is associated with a decrease in unmet outpatient care needs for rural residents, but it does not significantly affect medical service utilization among urban residents. This may be because the URRMI policy primarily benefits rural residents by expanding their coverage. Urban residents already have better healthcare services, so the policy does not significantly affect their medical service utilization. Despite employing Propensity Score Matching and Difference-in-Differences regression (PSM-DID) to minimize selection bias and simulate a randomized trial environment, this paper still faces some limitations. Firstly, the pre-policy period selected is 2011, and the post-policy period is 2015. However, during this period, only four provinces implement the Urban and Rural Resident Medical Insurance Scheme (URRMI). This results in a small sample size for the treatment group that may not be representative of a wider geographical area.

Fan et al. (2021) explore the impact of the integration of the Social Medical Insurance (ISMI) policy on health services utilization in rural China among middle-aged and elderly people. This study uses data from the 2011 and 2018 waves of the China Health and Retirement Longitudinal Study (CHARLS). In the 2011 wave, 12,145 observations with NRCMI coverage are selected, and in the 2018 wave, 12,705 observations of individuals who have experienced the ISMI are selected. The results show that following the implementation of the policy, the rate of inpatient health services utilization (IHSU) increases, while the rate of outpatient health services utilization (OHSU) decreases. The increase in inpatient health services utilization may be because the new policy made inpatient care more accessible and affordable for participants. The decrease in outpatient health services utilization may be due to patients receiving adequate inpatient treatment, reducing their need for outpatient visits. Additionally, there is an improvement in equity for outpatient services, and the policy appears to enhance the accessibility and affordability of inpatient services for lower-income groups. This paper has several limitations. First, it selects the 2011 wave of CHARLS data to represent the period before the implementation of the policy and the 2018 wave to represent the period after implementation. However, since most provinces began implementing the merger policy after 2016, incorporating the 2013 and 2015 waves of CHARLS data could help in providing a more detailed analysis of the transition period. Additionally, using cross-sectional data restricts the ability to draw causal conclusions from the findings. Finally, the study focuses only on rural residents, potentially limiting the applicability of its conclusions to urban populations.

Zhang et al. (2023) explore the effects of Urban and Rural Resident Basic Medical Insurance (URRBMI) integration on healthcare utilization and healthcare utilization inequality. The data for this study comes from the 2011 to 2018 waves of the CHARLS. The authors use a difference-in-differences approach in which the treatment group consists of provinces that adopt the integration from 2016 to 2017. The control group is made up of those provinces that were integrated after 2017. After excluding 5,774 participants living in provinces where the URRBMI was implemented before 2016, the analysis includes 17,708 participants. The results show that URRBMI is associated with higher inpatient visits and lower outpatient visits. This may be because the merged insurance policies provide more benefits for inpatient medical services. As a result, patients receive adequate inpatient care, reducing the need for outpatient visits. In addition, URRBMI is beneficial in improving healthcare utilization inequality among middle-aged and elderly people. This paper faces some limitations. Firstly, the implementation of URRMI as a pilot policy led to the exclusion of certain provinces from the sample due to a specific implementation timeline. This exclusion may potentially affect the representativeness of the sample, leading to potential bias in accurately assessing the overall effects of the policy. Additionally, considering data from only one period (2018 wave) after the policy implementation may not adequately capture the long-term effects.

Li et al. (2023) analyze the impact of public health insurance integration on healthcare utilization among adults aged 18-60 in China. The study utilizes 109,635 observations from the China Family Panel Studies (CFPS) from 2014 to 2020. The study examines two key outcomes: hospitalization in the past year and outpatient care in the past two weeks,

among individuals covered under the Urban Employee Basic Medical Insurance (UEBMI), the Urban Resident Basic Medical Insurance (URBMI), and the New Rural Cooperative Medical Scheme (NRCMS). The authors adopt a difference-in-differences approach. They use UEBMI as the control group and URBMI and NRCMS as the treatment groups. They assume URBMI and NRCMS individuals join the merged insurance scheme when their province implements it. After the merger policy was implemented, the results show a significant rise in inpatient service use among rural residents. This increase is especially notable among those with lower incomes. However, the analysis faces several limitations. The URRMI program started in 2010, and the impacts observed from 2014 to 2020 may not fully reflect the immediate effects of the policy integration, potentially overlooking variations in the early years. Additionally, the study's reliance on binary variables for measuring hospitalization and outpatient care fails to capture the depth and intensity of healthcare utilization, possibly oversimplifying the dynamics of healthcare use. A major concern is the choice of UEBMI participants as the control group. Using UEBMI as the control group introduces bias because UEBMI offers more comprehensive coverage and higher reimbursement rates than URBMI and NRCMS. This initial disparity can skew the DID model results.

3.3.2 Impact of Health Insurance on Children's Healthcare Utilization in the US.

Lave et al. (1998) examine the impact of Children's Health Insurance Programs (CHIPs) on healthcare utilization for newly enrolled children in the U.S. from 1995 to 1996. In this study, 1031 newly enrolled children are randomly selected from 29 counties of western Pennsylvania. Families of newly insured children are interviewed by phone at baseline, 6 months, and 12 months after enrolment, and a control group is interviewed

12 months after enrolment to assess the impact of health insurance. The main outcome variables include whether the child has a usual source of medical or dental care, the number of physician visits, and whether having unmet medical needs. The results show that after participating in CHIPs, regular medical and dental care rates improve significantly, and unmet medical requirements decrease. This could be because CHIPs precisely target the group that does not qualify for Medicaid but cannot afford private insurance, and it provides comprehensive coverage for services that children need, such as regular medical check-ups, dental care, and so on. These findings indicate a significant increase in children's access to medical treatment in the 12 months after enrolling in CHIPs, confirming the effectiveness of CHIP. The limitations of this study include the following: firstly, the sample scope is limited. The study mainly focuses on children who voluntarily participate in regional health insurance plans in western Pennsylvania, and these children are mostly from families with lower incomes. Therefore, the general applicability of the study results is limited. Secondly, some outcome variables, such as unmet medical needs, have strong subjectivity, which may affect the accuracy of the study results.

Kreider et al. (2016) compare the effect of different types of health insurance on healthcare access for children from lower- and middle-income families in the US. This research includes over 80,000 children aged less than 17 from the US National Surveys of Children's Health (NSCH). This study uses a repeated cross-sectional dataset over the years 2003, 2007, and 2011-2012. The insured status is divided into four categories: Medicaid, Children's Health Insurance Program (CHIP), private health insurance, and uninsured. The results show that over half of the children have private health insurance,

approximately 13% are covered by Medicaid, about 18% participate in CHIP, and about one in ten children do not have insurance. The authors find that children covered by Medicaid and CHIP are more likely than those covered by private insurance to receive preventive medical and dental services. These differences may be due to the fact that private insurance often has higher out-of-pocket costs and stricter service access restrictions, which may limit the accessibility and affordability of services. Therefore, Medicaid and CHIP may be better able to meet the medical needs of children due to their broader coverage and lower costs. This paper has several limitations. First, as the data used represent a repeated cross-section, only associations at different time points can be identified, and long-term trends or individual changes cannot be studied. Second, the study examines insurance status data at specific points, but the healthcare access is based on experiences from the previous 12 months. If a child's insurance status changed (for example, from uninsured to insured) during these 12 months, this time difference may lead to biased results and affect the accuracy of evaluating the effectiveness of the insurance.

Cassedy et al. (2008) explore the relationship between health insurance continuity and healthcare access and satisfaction for children aged 2 to 17 in the U.S. This study uses 12,270 observations from the Medical Expenditure Panel Survey data from 2000 to 2003. This study explores the impact of various insurance statuses, including continuous insurance, having an insurance gap, and continuous uninsurance, on children's medical care utilization. The results suggest that over half of the children have continuous private insurance, while approximately one-fifth have continuous public insurance. Furthermore, 6% of children are without insurance during the research period. Children who are

uninsured or have an insurance gap are much less likely to receive regular healthcare, attend childhood health examinations, and meet medical or prescription drug needs than those who have health insurance constantly. This may be because children's medical needs cannot be met when there is a gap in insurance coverage. These findings emphasize the importance of continuous health insurance for children to receive essential medical care. This paper has certain limitations. First, the measurement of whether there is an insurance gap may be subject to error. Since all health insurance statuses are collected at the end of the two-year study period, and insurance gaps can occur at any time during the two-year study period, which means that some insurance gaps may not be captured. Second, the study relies on participants reporting and discussing their unmet medical needs, and participants' memory errors or differences in understanding of the questions may still lead to inaccurate data.

3.3.3 Contributions

Firstly, existing research primarily focuses on healthcare utilization among adults, particularly middle-aged and older populations (e.g., Zhou et al., 2020; Lee et al., 2022). While some studies have examined children's healthcare utilization in the United States (e.g., Lave et al., 1998; Cassedy et al., 2008; Kreider et al., 2016), there is limited research in other countries, including China. Our study is the first to investigate the impact of health insurance on children's healthcare utilization within the Chinese context. Given the distinctive nature of China's health insurance system and the unique healthcare needs of children compared to adults, it is important to explore this topic in China. Unlike adults, children require more frequent preventive healthcare services, such as vaccinations and developmental screenings. Additionally, children's healthcare needs

often focus on managing acute illnesses and conditions unique to childhood. Despite these distinct needs, China does not currently have a dedicated health insurance scheme specifically designed for children. This raises important questions about whether the existing health insurance system effectively supports children's healthcare utilization and meets their unique requirements. Secondly, few studies have directly compared the impacts of public and private health insurance on healthcare utilization in China. This is partly due to the high prevalence of public health insurance. Although the overall participation rate in public health insurance is high, it is markedly lower for children than adults. This difference emphasizes the need for focused comparative studies on the impact of different health insurance schemes on children. This gap is significant because insurance type might influence children's healthcare utilization differently.

Previous evaluations of URRMI often used traditional DID methods with fixed points (e.g., Su et al., 2019; Zhang et al., 2023; Fan et al., 2021). These methods are limited by short post-implementation periods and may not accurately reflect the policy's actual effects due to artificially selected implementation time. For example, Su et al. (2019) chose 2011 as the pre-policy period and 2015 as the post-policy period. This short timeframe may not capture the long-term effects of the policy. Similarly, Fan et al. (2021) used the 2011 wave of CHARLS data to represent the period before the policy and the 2018 wave for after the policy. These methods overlook the variability in effects across provinces and the potential lag in policy impacts. Our study improves on this by employing a time-varying model using panel data that covers the policy from its initial pilot province to its implementation across almost all provinces. This comprehensive timeframe provides a dynamic analysis of the policy's phased implementation.

In addition, this is the first study to investigate the impact of the merger policy that combined URBMI and NRCMI schemes into URRMI on children's healthcare utilization. This offers new insights into how health insurance reforms affect children's access to medical services. This gap highlights an important area of study for understanding the effects of insurance policy shifts on children's healthcare access.

By addressing these gaps, this study aims to help us understand how health insurance affects children's use of healthcare in China. Therefore, the findings can support policy decisions and healthcare strategies.

3.4 Hypotheses

The availability of health insurance is often linked to increased access to healthcare services, as it reduces the financial barriers to seeking medical care (e.g., Zhou et al., 2020; Kreider et al., 2016; Lee et al., 2022; Zhang et al., 2020). Observationally, insured individuals tend to utilize healthcare services more frequently than those without insurance, due to the reduced cost burden and greater access to a range of healthcare providers. This trend is especially notable in pediatric healthcare, where insurance coverage is crucial for ensuring that children receive timely and necessary medical treatments (e.g., Huang and Liu, 2023; Lave et al., 1998; Cassedy et al., 2008). This pattern may partly reflect moral hazard or adverse selection. With insurance, individuals might use more healthcare due to lower costs, or because those needing more care are likelier to have insurance. (Cutler and Zeckhauser, 2000) This leads us to propose the following hypothesis:

Hypothesis 1: Children with health insurance are likely to have higher healthcare utilization rates compared to those without health insurance.

Public health insurance in China covers a wide range of basic health services, making it accessible and sufficient for routine health needs for a broad segment of the population. This broad coverage encourages frequent use of healthcare services within the public system. Conversely, private insurance provides added benefits like faster access to care, more choice in terms of healthcare providers, and services that go beyond the standard care covered by public schemes. However, it is typically utilized for supplementary or elective services that are not deemed essential, which does not necessarily increase overall healthcare utilization (Kreider et al.,2016). The higher costs associated with private healthcare can deter frequent use, limiting overall healthcare utilization compared to public insurance holders. Given these observations, we propose the following hypothesis:

Hypothesis 2: Children covered by public health insurance are likely to exhibit higher rates of healthcare service utilization compared to those covered by private health insurance.

The merger of urban and rural residents' basic medical insurance has harmonized healthcare benefits across rural and urban areas, enhancing administrative convenience for medical services. According to the State Council on the Integration of Urban and Rural Residents Basic Medical Insurance System (2016), this integration ensures that all reimbursement standards are now consistently aligned with the higher benchmarks. For example, in NRCMI, the reimbursement rate for inpatient care is between 55% and 75%.

While in URBMI, the reimbursement rate for inpatient care is around 70%. After merging into URRMI, the hospital reimbursement rate is about 75%. According to Xie et al.(2019), increases in the percentage of reimbursement rates and the scope of drug coverage have led to a reduction in out-of-pocket medical expenses, simplifying access to medical treatments. Additionally, Tan et al. (2019) argue that this merger policy broaden medical insurance-designated hospitals, significantly increasing the flexibility for residents to choose their preferred healthcare providers. Consequently, we anticipate that the URRMI will significantly boost healthcare utilization among children. This leads us to propose:

Hypothesis 3: The integration of Urban Resident Basic Medical Insurance (URBMI) and New Rural Cooperative Medical Insurance (NRCMI) into the unified Urban and Rural Resident Medical Insurance (URRMI) is associated with increased healthcare utilization rates among children.

3.5 Specifications and Methodology

3.5.1 Baseline Model

3.5.1.1 Insurance Status

To test Hypothesis 1, we examine the relationship between health insurance coverage and healthcare utilization. Following Currie and Gruber (1996), our model specification takes the following form:

$$utilization_dummy_{it}/healthcare_utilization_{it} = \alpha_1 * insured_{it} + \alpha_2 X_{it} + \lambda_i + p_t + \varepsilon_{it} \quad (3-1)$$

$utilization_dummy_{it}$ is a dummy variable that equals 1 if respondent i uses healthcare services at wave t , and 0 otherwise.

$healthcare_utilization_{it}$ is a continuous variable that represents the annual frequency of hospital visits for individual i at wave t .

$insured_{it}$ is a dummy variable with a value of 1 if the respondent i is covered by any type of health insurance at wave t and 0 otherwise.

The control variables (X_i) include: $male_{it}$, age_{it} , $urban_{it}$, $illness_occurrences_{it}$, l_income_{it} , $illterate_{it}$, $father_education_{it}$, $mother_education_{it}$

$male_{it}$ is a dummy variable equal to 1 for males and 0 otherwise. The coefficient associated with this variable is expected to be positive. Yan and Ren (2019) report that girls in rural China have lower healthcare utilization rates than boys, which is driven by the prevailing preference for sons.

age_{it} is the age of the individual i at time t . The coefficient associated with this variable is expected to be negative. Ishida et al. (2012) argue that the frequency of healthcare service use is significantly higher among younger children, especially those below two years. As children grow older, they use healthcare services less frequently. Adolescents between the ages of 13 and 17 have the lowest rate of using healthcare services.

$urban_{it}$ is a dummy variable, taking a value of 1 to represent respondents living in urban areas, and 0 otherwise. The coefficient associated with this variable is expected to be positive. Ma et al. (2021) identify a significant disparity between urban and rural

healthcare utilization in China, with urban residents typically enjoying better access and quality of care.

$illness_occurrences_{it}$ is a continuous variable representing the frequency of individual i being sick last month at time t . The coefficient associated with this variable is expected to be positive. Cayce et al. (2005) suggest that while routine health checks are a frequent part of children's healthcare utilization, conditions such as otitis media, acute upper respiratory infections, acute pharyngitis, and rhinitis are also significantly linked to the healthcare services accessed by children.

l_income_{it} is a continuous variable that indicates the logarithm of the average annual household income of individual i at time t . The coefficient associated with this variable is expected to be positive. Simpson et al. (2005) observe that children from low-income families have less access to regular medical and dental services compared to children from middle-to-high-income families.

$father_education_{it}/mother_education_{it}$: are continuous variables representing the father's/mother's highest education level of individual i at time t . The coefficient associated with this variable is expected to be positive. Ke et al. (2020) argue that the educational background of parents significantly influences medical care usage among children aged 0-14. Higher-educated mothers increase children's use of physical exams, while fathers with higher education levels enhance their children's access to preventive health guidance and improve their health outcomes.

u_i : This represents an individual fixed effect. Individual fixed effects capture individual-specific characteristics that remain constant throughout the study period.

v_t : This represents a time-fixed effect, which we control by adding time dummies in all our models.

ε_{it} : This is an idiosyncratic error term.

For Hypothesis 1 to hold, α_1 should be positive and significant.

3.5.1.2 Public vs Private Insurance

To test Hypothesis 2, we estimate the following Equation:

$$\begin{aligned} utilization_dummy_{it} / healthcare_utilization_{it} = & \beta_1 * public_health_insurance_{it} \\ & + \beta_2 * private_health_insurance_{it} + \beta_3 X_{it} + u_i + v_t + \mu_{it} \end{aligned} \quad (3-2)$$

$public_health_insurance_{it}$: A dummy variable with a value of 1 if the respondent is covered by public health insurance, and 0 otherwise.

$private_health_insurance_{it}$: A dummy variable with a value of 1 if the respondent is covered by private health insurance, and 0 otherwise.

X_{it} : contains the same control variables as Equation (3-1), namely $male_{it}$, age_{it} ,

$urban_{it}$, $illness_occurrences_{it}$, l_income_{it} , $father_education_{it}$,

$mother_education_{it}$

The structure of the error term remains consistent with the structure of Equation (3-1).

For Hypothesis 2 to hold, both β_1 and β_2 should be positive and significant, with β_1 expected to be greater than β_2 .

3.5.1.3 Merger Policy

To investigate the impact of merging the URBMI and NRCMI policies into URRMI on healthcare utilization rates, we choose a time-varying DID model to estimate Equation (3-3). The selection of this model is justified by two primary reasons. First, Athey and Imbens (2006) advocate for the use of the Difference-in-Differences (DID) approach in policy evaluation, highlighting its effectiveness in addressing issues of endogeneity. Second, since URRMI is a pilot policy implemented in phases across different provinces, a time-varying DID model is particularly suitable. Following Beck et al. (2010), our model is expressed as follows:

$$healthcare_utilization_{it}/utilization_dummy_{it} = \alpha_0 + \gamma_1 Treat_{it} + \gamma_2 X_{it} + v_i + \rho_t + \varepsilon_{it} \quad (3-3)$$

$Treat_{it}$ is a dummy variable with a value of 1 for the treatment group and 0 for the control group. The treatment group consists of individuals participating in URRMI at wave t , while the control group comprises those who do not participate in URRMI at wave t .

X_{it} : contains the same control variables as Equation (3-1), namely $male_{it}$, age_{it} , $urban_{it}$, $illness_occurrences_{it}$, l_income_{it} , $father_education_{it}$, $mother_education_{it}$

The structure of the error term remains consistent with the structure of Equation (3-1).

If Hypothesis 3 holds, γ_1 should be both significant and positive.

3.5.2 Estimation Methodology

To estimate equations (3-1), (3-2), and (3-3), we use a two-way fixed effects model that includes both wave (time) and individual fixed effects. This choice is due to its significant advantage in controlling for unobservable heterogeneity. The impact of time trends or policy changes that are common to all individuals is controlled for by using time-fixed effects, while individual fixed effects help eliminate bias due to traits that are invariant across individuals. As described by Wooldridge (2010), this dual approach effectively addresses some problems typically associated with panel analyses, such as omitted variable bias and measurement error. The combination of individual and time-fixed effects provides a more robust and reliable estimation, thereby enhancing the credibility of our findings.

To estimate Equation (3-1) and Equation (3-2), where the dependent variable is a binary indicator of healthcare utilization, we utilize the Linear Probability Model (LPM). The LPM is chosen for its straightforward interpretability, which is crucial for directly understanding the impact of changes in health insurance coverage on the probability of healthcare utilization. For robustness checks, we also apply a probit model to this binary indicator of healthcare utilization, ensuring our results are reliable across different statistical methods. Additionally, we chose the Poisson regression model to analyze another dependent variable, healthcare utilization frequency. This selection is given that the frequency of healthcare service visits, our dependent variable, exhibits

characteristics typical of count data, such as non-negative integers. Coxe et al. (2009) argue that when the dependent variable is a count with a mean value less than 10, standard ordinary least squares regression may produce biased results. Therefore, by employing the Poisson model, we can more accurately assess how variations in health insurance coverage affect the frequency of healthcare service visits.

3.6. Data and Descriptive Statistics

3.6.1 Data

Our study uses the 2010 through 2020 waves of the China Family Panel Survey (CFPS), covering separate questionnaires for children, adults, and families across 25 provinces. Specifically, our research concentrates on the children's questionnaire of the CFPS, targeting individuals under 16 years of age. This questionnaire is completed by parents for children up to 10 years old, and directly by children who are older than 10. This component of the survey gathers data on basic information, caregiving values, growth and development, health and medical care, educational expectations and plans, and the home environment. We first merge the child information with the corresponding family data for each survey wave. Then, we append these merged datasets across the six waves to form a comprehensive panel dataset with 49,717 observations. We use the Consumer Price Index (CPI) from the National Bureau of Statistics of China to adjust all monetary data for the economic variables in our study. This guarantees the consistency and comparability of our financial data throughout the years. Furthermore, we apply

winsorization to the top and bottom 1 percentage point of all continuous variables in order to control the impact of outliers in our analysis. We further refine the dataset by excluding observations that have missing values for essential regression variables, resulting in a final sample size of 43,432 observations used in our baseline regression analysis. The data processing steps are detailed in Figure 3.1. Table 3.1 contains definitions of all variables used in our paper.

3.6.2 Descriptive Statistics

Table 3.2 presents the descriptive statistics for all variables, including the sample size, mean, standard error, and the range of values, which includes both the minimum and maximum. From Column (2) of Table 3.2, we can see that 74.7% of our sample is insured. Specifically, within our sample, 69.4% participate in public health insurance, and 15.9% have private health insurance. Among public health insurance participants, the highest proportion is covered by NRCMI at 40.3%, followed by URRMI at 22.8%, and URBMI at 7.51%. The instrumental variable, provincial insurance participation rate, varies significantly, ranging from 36.3% to 95.2%. Public insurance provincial coverage also shows wide variation, from 27.8% to 93.8%, while average private insurance provincial rates is 15.9% and ranging from 1.65% to 54.3%. The demographic data reveals an average age of nearly 8. About 53.2% of our sample are male, and 41.1% live in urban areas. Parental education levels, measured on a scale from 1 to 9, show fathers on average slightly more educated (mean of 3.02) than mothers (mean of 2.85).

3.7 Results

3.7.1 Baseline Model Results

3.7.1.1 Insurance Status

Table 3.3 presents the estimates of Equation (3-1). Column 1 reports the results for the healthcare utilization dummy using a two-way fixed effects linear probability model, and Column 2 reports the results for healthcare utilization frequency using a two-way fixed effects Poisson regression model. In Column (1), the coefficient associated with the dummy indicating whether the child is insured is statistically significant and equal to 0.065, indicating that being insured is associated with a 6.5 percentage point higher probability of using healthcare services. In Column (2), the corresponding coefficient is also statistically significant and equal to 0.222, which indicates that being insured is associated with a 24.9¹⁸ percent increase in the frequency of healthcare utilization. This result is consistent with Zhou et al.(2020), who argue that individuals with health insurance generally utilize more healthcare services. The large coefficient could be explained by moral hazard. When individuals are insured, they might use more healthcare or rely less on preventive measures since costs are covered. In China, this often results in the overuse of services, such as unnecessary hospitalizations, excessive testing, and costly treatments. There's also supplier-induced demand, where doctors recommend more services because of insurance coverage (Wagstaff and Lindelow, 2008). This is also consistent with our Hypothesis 1.

¹⁸ The economic impact on healthcare utilization frequency is calculated as the percentage change resulting from whether or not an individual has insurance. Specifically, the 24.9% increase is derived by converting the coefficient to a percentage: $e^{0.222} - 1 \approx 0.249$.

Furthermore, in column (1), the coefficient of age is statistically significant and equal to -0.029, indicating that each additional year of age is associated with a 2.9 percentage point lower probability of using healthcare utilization. This is in line with our expectations and consistent with the argument by Ishida et al. (2012), who argue that as children grow older, they use healthcare services less frequently. Columns (1) and (2) of Table 3.3 jointly confirm a positive correlation between the incidence of illnesses and the use of healthcare services among children, evaluated through both a dummy variable and frequency of utilization. This correlation supports findings by Cayce et al. (2005), who noted that conditions such as otitis media, acute upper respiratory infections, acute pharyngitis, and rhinitis significantly influence the healthcare services utilized by children.

The results for educational variables show that higher levels of the father's education are positively correlated with the frequency of healthcare utilization. This finding is consistent with Ke et al. (2020), who argue that the educational background of parents significantly increases medical care usage among children. However, higher levels of the mother's education are negatively associated with children's healthcare services usage. This may be because higher education levels in mothers may lead to increased health literacy, enabling them to manage minor health issues more effectively at home, thus reducing the frequency of healthcare utilization for their children.

3.7.1.2 Public and Private Health Insurance

Table 3.4 shows the estimates of Equation (3-2), which examines the effect of public and private health insurance on healthcare utilization. Column 1 presents the coefficients of the two-way fixed effect linear probability model in the case in which the dependent

variable is the healthcare utilization dummy. Column 2 displays the coefficients of the two-way fixed effects Poisson regression model for the case in which the dependent variable is healthcare utilization frequency. In Column (1), the coefficient associated with public health insurance is statistically significant and equal to 0.063, indicating that having public health insurance is associated with a 6.3 percentage point higher probability of utilizing healthcare services. By contrast, having private health insurance is associated with a 2.3 percentage point higher probability of using healthcare services. We use an F-test to compare the effects of public and private health insurance on healthcare utilization. The test results indicate a significant difference between the two effects ($F = 13.81$, $p = 0.0002$), demonstrating that public health insurance significantly impacts healthcare utilization more than private health insurance. This implies that children covered by public health insurance are more likely to use healthcare services compared to those with private health insurance, which is consistent with our Hypothesis 2. In Column (2), the coefficient for public health insurance is statistically significant and equal to 0.218, which indicates that having public health insurance is associated with a 24.4¹⁹ percent increase in the frequency of healthcare utilization. By contrast, having private health insurance has no significant impact on the frequency of healthcare utilization. This emphasizes the critical role of public health insurance in China, which likely promotes higher utilization among children due to its affordability and accessibility. By contrast, private health insurance might not enhance overall utilization rates, given its more limited scope and focus on services beyond basic care.

¹⁹ The 24.4% increase is derived by converting the coefficient to a percentage: $e^{0.218} - 1 \approx 0.244$.

The coefficients associated with the control variables are similar to those in Table 3.3.

3.7.1.3 DID Model

Main results. Next, we discuss the estimates of our time-varying DID model illustrated in Equation (3-3), which aims to assess the effect of merging the URBMI and NRCMI schemes into the URRMI scheme on child healthcare utilization. The results are reported in Table 3.5. Column 1 displays the estimates when the dependent variable is the healthcare utilization dummy, while Column 2 presents the estimates of the determinants of the healthcare utilization frequency. $Treat_{it}$ is a dummy variable equal to 1 if an individual is covered under the merged URRMI policy at wave t , and 0 otherwise. The treatment group accounts for 27.6 percent of the sample. In Column (1), we can observe that being covered under the merged URRMI policy is associated with a 3.1 percentage point higher probability of using healthcare services, compared to those not covered by the merged policy. Column (2) shows that being covered under the merged URRMI policy is associated with a 8.9²⁰ percent higher frequency of using healthcare services. This may be due to the improved integration and coordination of services after the insurance merger, which reduced administrative barriers and enhanced access to healthcare services between urban and rural areas. Additionally, the merged insurance policy follows a highest reimbursement standards than the two previous policies, further lowering the barriers to utilizing healthcare services. Consequently, the URRMI policy may have made it easier for insured individuals to seek and use healthcare services, leading to an increased utilization rate. This is consistent with our Hypothesis 3, as well

²⁰ The 8.9% increase is derived by converting the coefficient to a percentage: $e^{0.085} - 1 \approx 0.089$.

as with Fan et al. (2021) and Zhang et al. (2023), who argue that the merger policy is associated with higher rates of inpatient visits. Once again, the coefficients associated with the control variables are similar to those reported in Table 3.3.

Parallel trends testing. Parallel trend testing is essential for the DID model as it relies on the assumption that, before treatment, the outcome trends of the treatment and control groups are parallel (Abadie, 2005). Using Event Study Analysis (ESA) with DID allows for precise testing of parallel trends (Beck et al., 2010; Liu et al., 2022). Furthermore, this approach provides insights into the policy's dynamic effects both before and after implementation. The specific regression formulas used to test the parallel trends assumption are outlined below.

$$\text{healthcare_utilization}_{it}/\text{utilization_dummy}_{it} = \beta_0 + \beta_1 D_{it}^{-5} + \beta_2 D_{it}^{-4} + \beta_3 D_{it}^{-3} + \beta_4 D_{it}^{-2} + \beta_5 D_{it}^{-1} + \beta_6 D_{it}^1 + \beta_7 D_{it}^2 + \beta_8 D_{it}^3 + \beta_9 D_{it}^4 + \beta_{10} D_{it}^5 + \beta_{11} X_{it} + v_i + \rho_t + \varepsilon_{it} \quad (3-4)$$

D_{it}^{-i} : dummy variable equal to 1 i periods before individual i started participating in the URRMI at time t , and 0 otherwise.

D_{it}^i : dummy variable equal to 1 i periods after individual i started participating in the URRMI at time t , and 0 otherwise.

In Figure 3.2, the vertical axis represents the healthcare utilization dummy, and the horizontal axis represents the time before and after the implementation of the policy. The five periods preceding the policy implementation show that the coefficients ($\beta_1, \beta_2, \beta_3, \beta_4, \beta_5$) in Equation (3-4) are not significant. This indicates that the differences

between the treatment group (participating in URRMI) and the control group before the implementation of the policy are not statistically significant. Hence, the two groups are comparable before the policy change, meeting the assumption of parallel trends. From Figure 3.2, we can also observe that the coefficients become significant after the merger policy is implemented. This suggests that the merger policy has a statistically significant impact on healthcare utilization.

In Figure 3.3, the vertical axis represents healthcare utilization frequency, while the horizontal axis remains the same as in Figure 3.2. In the five periods preceding the policy implementation, all coefficients ($\beta_1, \beta_2, \beta_3, \beta_4, \beta_5$) of Equation (3-4) are also not significant. This indicates no difference in healthcare utilization frequency before the implementation of the URRMI policy, confirming that our model meets the parallel trends assumption. In addition, the coefficients ($\alpha_1, \alpha_2, \alpha_3$) of Equation (3-4) are all significant after the merger policy is implemented. This confirms that the merger policy has a significant impact on healthcare utilization frequency.

Overall, this event study analysis helps validate our DID estimates by confirming that the treatment and control groups are comparable before the URRMI policy implementation and that the policy significantly impacts healthcare utilization after the URRMI implementation.

Placebo Test. The placebo test is used to further validate the DID approach. The basic idea behind this test is to regress a "fake" treatment group against a "fake" treatment time. To create a "fake" treatment group, we randomly select a number of subsamples equal to the real treatment group who participated in URRMI. Each subsample is

assigned a random year of URRMI participation to serve as a 'fake' treatment year. This process is repeated 500 times to calculate p-values and regression coefficients for the following regression:

$$\begin{aligned} \text{healthcare_utilization}_{it}/\text{utilization_dummy}_{it} = & \beta_0 + \beta_1 \text{Fake_Treat}_{it} + \\ & \beta_2 X_{it} + v_i + \rho_t + \varepsilon_{it} \end{aligned} \quad (3-5)$$

We can see that compared to Equation (3-3), the only difference in Equation (3-5) is that Treat_{it} is replaced by Fake_Treat_{it} . Fake_Treat_{it} is a dummy variable equal to 1 for the "fake" treatment group, and 0 otherwise. If most of 500-times β_1 with the "fake" treatment group estimates obtained from Equation (3-5) are not significant, and the regression coefficients are mostly different from the actual regression coefficient 0.031/0.085 (α_1 of Equation (3-3)), it indicates that our baseline DID model's regression results are not due to random chance.

Figure 3.4 shows the distribution of the 500 estimated coefficients (β_1) of Equation (3-5) and their corresponding p-values for the utilization dummy. Figure 3.5 presents the same for healthcare utilization frequency.

In Figure 3.4, the x-axis represents the magnitude of the estimated coefficients (β_1), while the y-axis represents the density values and p-values. We observe that the vast majority of points in Figure 3.4 are located above the 0.1 line, indicating that the majority of p-values are greater than 0.1. A p-value threshold of 0.1 indicates a rather conservative level of statistical significance, and this implies that the majority of estimated coefficients (β_1) are not statistically significant. Additionally, we can observe that the majority of coefficient values (β_1) are different from our actual coefficient of

0.031 (α_1 of Equation (3-3)). This demonstrates that our DID model's results are reliable and not due to random chance.

In Figure 3.5, we observe that the vast majority of p-values are located above the 0.1 line, indicating that the majority of estimated coefficients (β_1) are not significant. Furthermore, most coefficient values (β_1) are smaller than our actual coefficient of 0.089 (α_1 of Equation (3-3)). This implies that our results are not due to random chance.

Thus, the placebo test supports the validity of our findings by confirming that the positive significant effects of health insurance on the utilization dummy or healthcare utilization frequency are not caused by random variations but are most likely due to the implementation of the URRMI policy.

3.7.2 Robustness Checks

3.7.2.1 Two-part Model Results

One of our dependent variables is the frequency of healthcare service utilization. Yet, there are a significant number of individuals who do not use healthcare services at all within a year. According to our sample, 49.8% of the respondents did not make any healthcare visits. The two-part model helps us distinguish healthcare users from non-users. Therefore, following the approach of Leung and Yu (1996), we employ the two-part model in our study as a robustness test to handle the zero-inflated nature of healthcare utilization data. According to Mullahy (1998), the two-part model is

commonly used in the analysis of healthcare data, describing the rate of hospitalizations, surgeries, and doctor visits.

Specifically, the first part of the model is a binary selection model that estimates the probability of having zero healthcare service utilization. We use the Correlated Random Effect (CRE) Probit model to estimate the determinants of the utilization dummy for Equation (3-1) and Equation (3-2). The CRE Probit model can also serve as a robustness check for the two-way fixed effects linear probability model in our baseline analysis.

The second part is a zero-truncated Poisson regression model. We use a two-way fixed effects model to estimate the determinants of healthcare utilization frequency of Equations (3-1) and (3-2) among healthcare users. The difference between this part and our baseline model is that the zero-truncated Poisson regression model includes only individuals who use healthcare services in the sample. Consequently, this model also serves as a robustness check for our baseline Poisson regression model when applied to the entire sample.

By using this two-part model approach, we can effectively address the presence of zero values in the healthcare utilization data and provide more accurate estimates of the factors influencing healthcare service use.

Table 3.6 presents the estimation results for the two-part model. Column 1 shows the CRE probit estimation results of Equation (3-1), which assesses the determinants of the probability of healthcare utilization. Column 2 provides the two-way fixed effect Poisson regression model to estimate the determinants of healthcare utilization frequency of Equations (3-1), conditional on having used healthcare services. From Column (1), we

can see that the marginal effect associated with the dummy for being insured is statistically significant and equal to 0.087, indicating that insurance status is positively associated with the likelihood of healthcare utilization. This aligns with the estimation of the two-way fixed effect LPM (Linear Probability Model) in our baseline model. In Column (2), the coefficient for being insured is statistically significant and equal to 0.098, suggesting that insured children have a about 10.3²¹ percent higher healthcare utilization frequency among healthcare users. This is consistent with our previous baseline findings and further confirms the robustness of our results when considering both healthcare users and non-users.

As for control variables, column (1) shows a positive association between males and healthcare utilization, indicating that males are associated with a 2.4 percentage point higher probability of using healthcare utilization. This is consistent with Yan and Ren (2019) who also argue that boys have higher healthcare utilization rates than girls in China. In column (2), family income has a significant positive impact on healthcare utilization frequency among healthcare users. This is consistent with Simpson et al. (2005) who also argue that compared to children from middle-to-high-income families, children from low-income families have less access to healthcare utilization. In addition, the effects of other variables are generally consistent with our previous results.

Table 3.7 presents the estimation results for the two-part model when considering the impact of public health insurance and private health insurance. Column 1 presents the CRE probit estimation results of Equation (3-2), which assesses the determinants of the

²¹ The 10.3% increase is derived by converting the coefficient to a percentage: $e^{0.098} - 1 \approx 0.103$

probability of healthcare utilization. Column 2 provides the two-way fixed effect Poisson regression model to estimate the determinants of healthcare utilization frequency of Equations (3-2), conditional on having used healthcare services. From Column (1), the coefficient associated with the public health insurance dummy is statistically significant and equal to 0.083, while the coefficient associated with the private health insurance dummy is also statistically significant and equal to 0.031. The F-test results also indicate a significant difference between the effects of public health insurance and private health insurance. In Column (2), for healthcare users, public health insurance still has a significant and positive impact. However, the coefficient associated with private health insurance is no longer significant. This could imply that private health insurance primarily influences the decision to seek care rather than the intensity of care received. According to Colombo and Tapay (2004), private health insurance offers benefits like faster access and a broader choice of providers, which improves initial healthcare access but does not necessarily increase overall utilisation due to higher related costs and coverage concentrated on non-essential treatments. Overall, these findings emphasize the important role of public health insurance in increasing healthcare accessibility and utilization among children.

In addition, the coefficients associated with the control variables are similar to those shown in the previous table.

3.7.2.2 Control Function Approach Results

To address the potential endogeneity problem arising from selection bias and reverse causality, where individuals who anticipate higher healthcare needs are more likely to purchase insurance, and those insured may increase their healthcare usage, we employ the Control Function (CF) Approach. According to Wooldridge (2015), we chose the CF approach because our baseline models include non-linear terms. Two-Stage Least Squares (2SLS) is only suitable for linear models, and it can lead to bias and inconsistency in non-linear models. Therefore, 2SLS is not appropriate for our analysis.

In the first stage, to correct for the potential endogeneity of the variable $insured_{it}$ in Equation (3-1), we use the provincial insurance coverage rates as an instrument. Individual insurance status can be endogenous because personal health expectations or pre-existing conditions might influence both an individual's decision to obtain insurance and their subsequent healthcare utilization. Provincial insurance coverage rates can be effective instruments because they are exogenous to personal insurance choices, and these rates are also closely related to individual insurance uptake. Our choice is supported by Liu and Zhao (2014), who use the URBMI coverage rates across provinces as an instrumental variable to examine the impact of Urban Resident Basic Medical Insurance (URBMI) on healthcare utilization. The first stage regression model is specified as follows:

$$insured_{it} = \alpha_0 + \alpha_1 insured_rate_{it} + \alpha_2 X_{it} + \lambda_i + \mu_t + \varepsilon_{it} \quad (3-6)$$

In the second stage, the residual from the first stage ($residual_{it}$) regression is included as an additional regressor in the baseline model, which leads to the following Equation:

$$\begin{aligned} \text{healthcare_utilization}_{it}/\text{utilization_dummy}_{it} = & \beta_0 + \beta_1 \text{insured}_{it} + \beta_2 \text{residual}_{it} \\ & + \beta_3 X_{it} \gamma_i + \rho_t + \eta_{it} \end{aligned} \quad (3-7)$$

The CF method effectively handles endogeneity in both linear and non-linear models by introducing the residuals from the first-stage regression into the second-stage regression. We generally expect the first-stage residuals to be significant in the second-stage model. This is because these residuals represent the part of the endogenous variable that is not explained by the instrumental variable. If these residuals are significant in the second stage of regression, this indicates that the control function correctly captures the effects of endogenous variables, effectively removing endogeneity bias from the model. Additionally, a significant chi-square test of the residual term strongly suggests that the inclusion of the residual term is necessary. Unlike the significance of the residual term in the second stage, this chi-square test assesses the overall contribution and relevance of the residuals to the model's explanatory power.

Next, to correct for the potential endogeneity of the insurance variables (*Public_Health_Insurance_{it}*, *Private_Health_Insurance_{it}*) in Equation (3-2), we use the provincial public and private insurance coverage rates as instruments. In the second stage, the residual from the first stage (*residual_public_{it}*, *residual_private_{it}*) are included as additional regressors in the main model, leading to the following model:

$$\begin{aligned} \text{healthcare_utilization}_{it}/\text{utilization_dummy}_{it} = & \beta_1 \text{Public_Health_Insurance}_{it} \\ & + \beta_2 \text{Private_Health_Insurance}_{it} + \beta_3 \text{residual_public}_{it} + \beta_4 \text{residual_private}_{it} + \\ & \beta_5 X_{it} + u_i + v_t + \mu_{it} \end{aligned} \quad (3-8)$$

Table 3.8 presents the estimates of Equation (3-7). Column 1 displays the results for the determinants of the healthcare utilization dummy obtained using the CRE probit model, while Column 2 presents the outcomes for healthcare utilization frequency estimated by the two-way fixed effect Poisson regression model. In Column (1), we can observe that the marginal effect associated with the insured dummy is statistically significant and equal to 0.077, this indicates that being insured is associated with a 7.7 percentage point increase in the probability of using healthcare services, after accounting for endogeneity using the Control Function approach. Similarly consistent impacts are observed across other models, with the two-way fixed effects LPM model showing an effect of 0.065 and the CRE probit model showing 0.087. In Column (2), the coefficient associated with the insured dummy is also statistically significant and equal to 0.217. This suggests that being insured is associated with a higher healthcare utilization rate. The positive relationships between health insurance and healthcare utilization frequency are also consistent with our hypotheses and the baseline model results. Notably, this coefficient is considerably smaller than the baseline model's 0.222. This reduction suggests that the control function model may effectively address the issue of adverse selection, as it likely captures the endogenous variation related to health needs that may have inflated the coefficient in the baseline model.

The marginal effect associated with the residual term is statistically significant and equal to 0.125 in Column (1). In Column (2), the coefficient associated with the residual term is also statistically significant and equal to 0.110. These findings suggest that unobserved factors, as captured by the residuals, are positively associated with both the probability of healthcare utilization and the frequency of healthcare use. Moreover, the Chi-squared

test for the residual term ($\text{Chi}^2 = 171.97$, $p < 0.000$) in Column (1) and ($\text{Chi}^2 = 61.30$, $p < 0.000$) in Column (2). In our study, the Chi-squared test examines whether the inclusion of the residuals from the first-stage regression significantly improves the model's predictive accuracy. According to Wooldridge (2015), these results jointly confirm the presence of endogeneity in the health insurance variable and demonstrate the effectiveness of the Control Function approach in managing and resolving this endogeneity.

Table A3.11 in the Appendix presents the first-stage CRE probit regression estimates of Equation (3-6). In Column (1), we can observe that the marginal effect associated with the province-level insurance rate is statistically significant and equal to 0.857. This result indicates a significant positive association between the individual insurance status and the provincial-level health insurance participation rate. This suggests that the provincial health insurance participation rate is a strong instrument for individual insurance status in our model.

Table 3.9 shows the results of the Control Function Approach estimates of Equation (3-8). Column 1 displays the results for the healthcare utilization dummy obtained using the CRE probit model, while Column 2 presents the estimates for the determinants of the healthcare utilization frequency obtained using the two-way fixed effect Poisson regression model. The marginal effect associated with the public (private) health insurance dummy is statistically significant and equal to 0.071 (0.031) in Column (1). The difference in the effect of the two insurance variables implies that children covered by public health insurance have a higher probability of using healthcare services. These

findings are consistent with the results from our two-way fixed effects LPM model (0.063, 0.023) and CRE probit model (0.083, 0.031), further confirming the distinct impacts of each type of insurance. In Column 2, the coefficient associated with public health insurance is also statistically significant and equal to 0.212. The coefficient for private health insurance remains statistically insignificant. This suggests that private health insurance does not significantly influence the frequency of healthcare utilization, even after adjusting for potential endogeneity.

We also observe a significant and positive correlation between the coefficients associated with the residual term of both the private and public health insurance regressions in column (1). The significant residual for public health insurance in column (2), and not for private health insurance, could suggest that private insurance itself does not substantially influence healthcare utilization frequency. In addition, the chi-squared tests for all residuals, except for the private insurance residual in column (2), are statistically significant. These results confirm that the inclusion of residual terms is appropriate, which enhances the explanatory power of the model.

Furthermore, Table A3.12 in the Appendix presents the first-stage CRE probit regression estimates of Equation (3-6). In Column (1), we observe that the marginal effect associated with the province-level public health insurance rate is statistically significant and equal to 0.909. In Column (2), we observe that the marginal effect associated with the province-level private health insurance rate is statistically significant and equal to 0.669. These results suggest that the provincial public/private health insurance participation rate is a strong instrument for the individual public/private insurance status.

In addition, the marginal effects/coefficients associated with the control variables are similar to those shown in the previous tables.

3.7.3 Further Exploration of Healthcare Utilization Inequalities for Insured and Uninsured Children

We hereafter explore the impact of insurance status on income-related inequalities in children's healthcare utilization.

The degree of healthcare utilization inequalities is usually measured by the concentration index (CI). According to Wagstaff et al. (1991), the CI can help to assess differences in health distribution among populations with different socio-economic statuses. Also, Wagstaff and Doorslaer (2000) point out that using the CI to measure healthcare utilization requires adjusting actual utilization by the expected utilization obtained from regression analysis. The main goal is to eliminate differences in healthcare utilization caused by demand factors like age, gender, and health status.

Specifically, following Wagstaff et al. (2007), we calculate demand-standardized healthcare utilization. First, we estimate Equation (3-1) to get the expected frequency of healthcare use. Next, we subtract the expected utilization frequency from the actual utilization frequency to determine the deviation from expected use. Finally, we add the average actual utilization frequency of the entire sample to the deviation. By doing so, we ensure that the standardized healthcare utilization measure retains the same average

as actual utilization frequency. We denote the standardized healthcare utilization frequency as f_i .

Next, we calculate the concentration index based on the standardized utilization frequency. We sort the children by household income from low to high, obtaining each child's relative income rank r_i . Then, we compute the covariance between standardized healthcare utilization frequency f_i and the income rank r_i , denoted as $cov(f_i, r_i)$. Finally, we calculate the average of f_i , which is $\bar{f}$. The CI is then given by the following formula:

$$CI = \frac{2}{\bar{f}} \cdot cov(f_i, r_i)$$

The CI ranges from -1 to 1. When the CI equals 0, it means healthcare utilization is equally distributed among different income groups. If $CI > 0$, it indicates inequality, with more utilization concentrated among high-income groups. If $CI < 0$, it shows more utilization is concentrated among low-income groups.

By comparing the CI of insured and uninsured children, we can analyze how health insurance affects income-related inequalities in healthcare utilization. For insured children, we further compare the treatment group (those participating in URRMI) and the control group, urban and rural areas, and provinces with high and low GRP (Gross Regional Product). We focus on these specific groups because, although all groups are insured, there are disparities in their insurance policies that may affect healthcare utilization.

Table 3.10 shows the CI values measuring income-related inequalities in children's healthcare utilization across various groups. Firstly, we observe that in the whole sample, the total CI is significant and equal to 0.014. This indicates that children from higher-income families tend to use more healthcare services in the whole sample, even after adjusting for demand factors. In row (1), we compare the CI values for children insured by any type of health insurance with those who are uninsured. We observe that the CI for uninsured children is statistically significant and equal to 0.020. This suggests that uninsured children from higher-income families utilize more healthcare services than those from lower-income families. For insured children, the CI is statistically significant and equal to 0.007. Although this value is still greater than zero, it is much lower than the CI for uninsured children. The difference in CI between insured and uninsured children is statistically significant and equal to -0.013. This indicates that health insurance plays a significant role in mitigating healthcare utilization inequality. This may be because health insurance can cover part of the medical cost, making it easier for low-income families to afford medical costs. This is consistent with Zhou et al. (2014), who argue that UEBMI and URBMI are effective in reducing pro-rich inequality in inpatient utilization in Shanxi province.

In row (2), we compare insured children in the treatment group, whose insurance was merged into URRMI, with the control group. The CI for the treatment group is statistically significant and equal to -0.035, indicating that lower-income children use more healthcare services than higher-income children. For the control group, the CI is 0.021, showing healthcare utilization inequality, with higher-income children utilizing more services. The difference between the two groups is statistically significant and equal to -

0.055, suggesting that the URRMI significantly reduces and even reverses income-related inequalities in healthcare utilization. This is supported by Li et al. (2019), who argue that the concentration index for inpatient frequency shifted to pro-poor after the integration. Additionally, Zhang et al. (2023) point out that the merger policy URRMI leads to pro-poor inequality among middle-aged and elderly people. They explain this by highlighting that the URRMI merger expanded insurance coverage and improved inpatient and outpatient reimbursement rates, benefiting lower-income groups who were sensitive to medical costs before the merger. This higher sensitivity means that children from lower-income families previously had unmet medical needs due to financial barriers. With the merger, healthcare services are more accessible and affordable for them, resulting in a significant rise in healthcare utilization. By contrast, higher-income groups are less affected by these financial barriers and already have adequate access to healthcare services. Consequently, their utilization rates remained relatively stable even after the insurance merger. As a result, healthcare utilization became more concentrated among children from low-income families in the treatment group. This shift indicates that the merger effectively addressed the unmet healthcare needs of lower-income populations, thereby increasing their use of healthcare services.

In row (3), we compare insured children in rural and urban areas. The CI for rural areas is statistically significant and equal to 0.017, meaning higher-income children in rural areas use more healthcare services. In urban areas, the CI is -0.006, which is not statistically significant. This suggests that healthcare utilization is nearly equal across income groups in urban areas. This indicates that, among insured children, healthcare utilization inequalities are more significant in rural areas. This may be because there are

relatively fewer healthcare resources in rural areas compared to urban areas. Additionally, before the insurance merger, NRCMS provided lower benefits than urban health insurance programs (URBMI and UEBMI). As a result, low-income families in rural areas find it hard to access medical services even if they have insurance.

In row (4), we explore differences among insured children in provinces with high and low GRP. In low GRP provinces, the CI is statistically significant and equal to 0.014, indicating a pro-rich healthcare inequality. In high GRP provinces, the CI is -0.004 and not statistically significant. This shows a more equal distribution of healthcare utilization in economically developed provinces. The difference indicates that income-related inequalities are more severe in provinces with lower economic development. This may be due to the fact that health insurance policies vary from province to province in China, in terms of thresholds, reimbursement rates, and caps. Furthermore, according to Chen et al. (2014), the local financial situation can influence each province's health insurance policies and local healthcare resources. In addition, in provinces with higher GRP, the proportion of low-income families is smaller compared to provinces with lower GRP (Yan and Mohd, 2023), which may also help explain why healthcare inequalities are more severe in less developed provinces.

Overall, after adjusting for demand factors, there is still some inequality in healthcare utilization that favors wealthier families in the entire sample. However, this inequality is significantly smaller among insured children compared to uninsured children. Specifically, among the insured, children covered by the merger program tend to have higher healthcare utilization if they are from lower-income families. Furthermore, among

insured children, healthcare utilization in urban areas and provinces with higher GRP is generally fair and does not depend much on family income. In contrast, in rural areas and provinces with lower GRP, healthcare utilization still shows inequality that favors wealthier families.

3.8. Conclusion and Policy Implications

This paper evaluates the effects of health insurance policies in China on child healthcare utilization. We reach the following conclusions:

Firstly, Children with health insurance exhibit a higher likelihood and greater frequency of healthcare utilization compared to uninsured children. This finding suggests that health insurance effectively enhances healthcare access among children in China. These results are robust to using a control function approach and a two-part model, underscoring the important role of health insurance in improving children's healthcare access.

Secondly, children covered by public health insurance exhibit a higher probability of using healthcare services compared to those with private health insurance. This likely reflects the greater affordability and accessibility of public health insurance in China. In contrast, although private health insurance generally provides access to specialized services, it does not necessarily translate into higher overall utilization due to its more limited scope and emphasis on non-basic care services.

Thirdly, the integration of Urban Resident Basic Medical Insurance (URBMI) and New Rural Cooperative Medical Insurance (NRCMI) into the unified Urban and Rural Resident Medical Insurance (URRMI) is linked to increased healthcare utilization among children. This improvement may result from better integration and coordination of services following the insurance merger, which minimized administrative barriers and enhanced healthcare access across urban and rural areas. The unified policy, adopting the most generous reimbursement standards of the former policies, likely reduced financial barriers to healthcare access, contributing to higher utilization rates.

Finally, Inequality in healthcare access is much smaller among insured children compared to uninsured ones. Insured children from lower-income families have higher healthcare utilization, particularly under the merger program. In urban areas and wealthier provinces, healthcare use is generally equitable and less influenced by family income. However, in rural areas and poorer provinces, healthcare access still favors wealthier families.

Based on our findings, we make the following policy recommendations. First and foremost, it is crucial to implement measures aimed at extending the coverage of child health insurance, thereby ensuring that a greater number of children have access to essential healthcare services. Child-specific health insurance policies can be designed to better meet children's unique healthcare needs, such as their frequent need for preventative check-ups and outpatient care. Furthermore, given the positive impact of public health insurance, it is crucial to promote the adoption of the public health insurance policy across all cities in China, enhancing accessibility and equity in child

healthcare. In addition, the expansion of unified health insurance policies like URRMI should be promoted across all regions. This expansion should include efforts to improve inter-sectoral collaboration, which will enhance the coordination of healthcare services between urban and rural areas. It is also important to regularly evaluate the effectiveness of these policies and continuously adapt them to meet the evolving healthcare needs of children.

Finally, policies should aim to ensure that both low-income and rural residents receive equal healthcare opportunities as those in wealthier urban areas. Furthermore, policymakers should expand health insurance coverage in rural and low-income areas to reduce healthcare inequalities. For example, providing discounts for health insurance and simplifying access will encourage higher healthcare utilization for children from low-income families. Adjusting reimbursement rates for essential care can help make healthcare more affordable for these groups. These measures could help address disparities in healthcare access and utilization.

Our study has certain limitations. Due to data constraints, we could not assess inpatient and outpatient services comprehensively. Additionally, the data collection method via the CFPS questionnaire, completed by parents for children up to 10 years old and directly by older children, may introduce some reporting bias.

Future studies should explore the impact of health insurance on the quality of healthcare services provided. This could provide deeper insights into how insurance policies affect healthcare outcomes beyond utilization rates.

Figures and Tables for Chapter 3

Figure 3.1 Data Process Steps

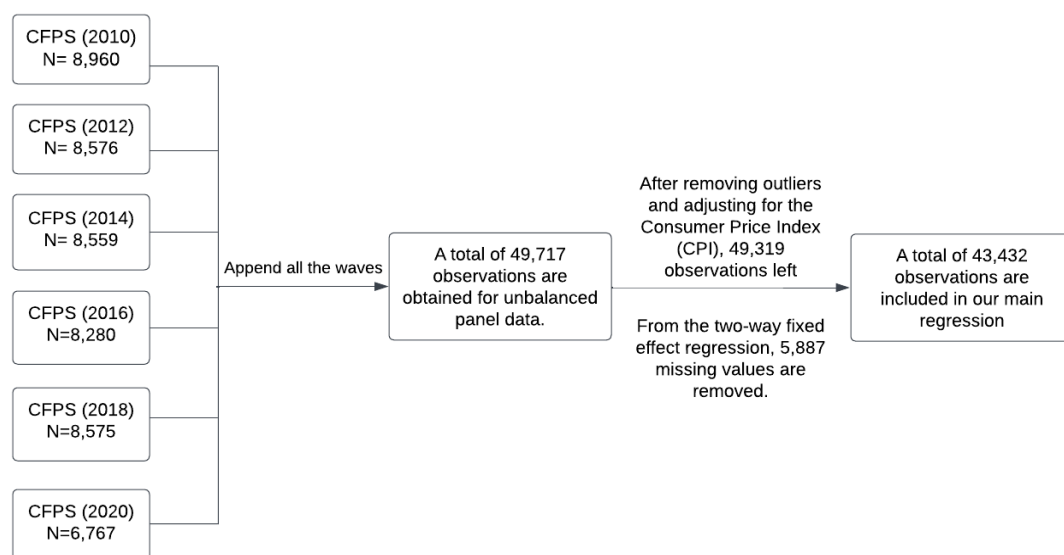


Figure 3.2 Event Study (Healthcare Utilization Dummy)

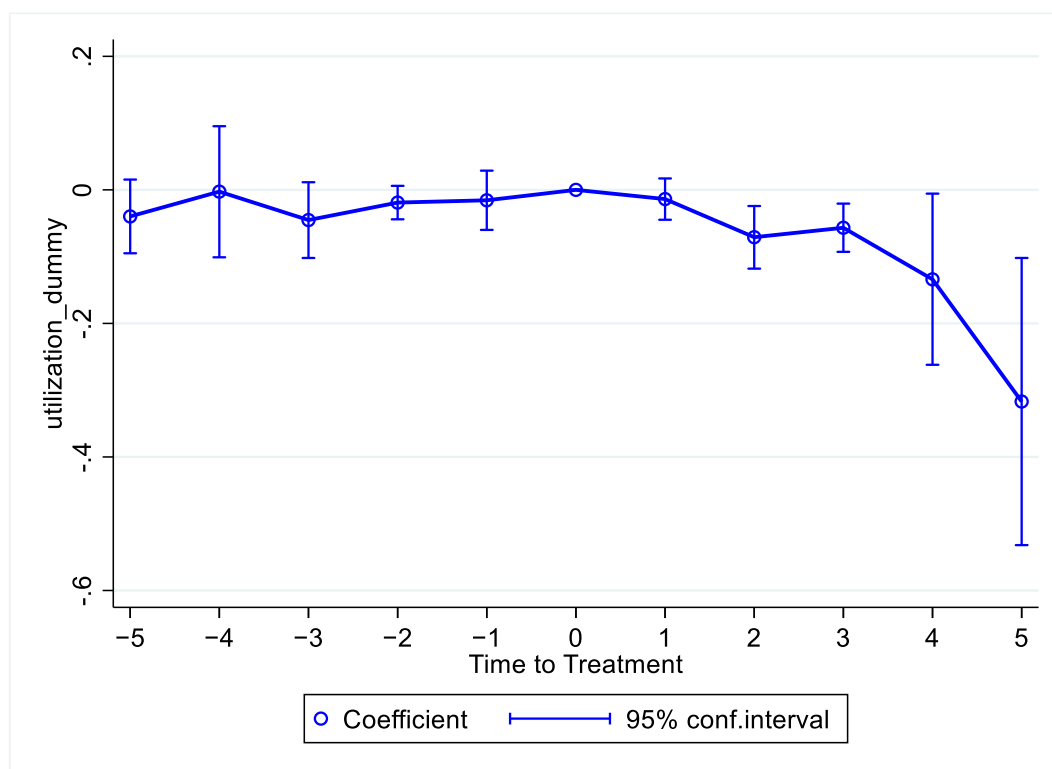


Figure 3.3 Event Study (Healthcare Utilization Frequency)

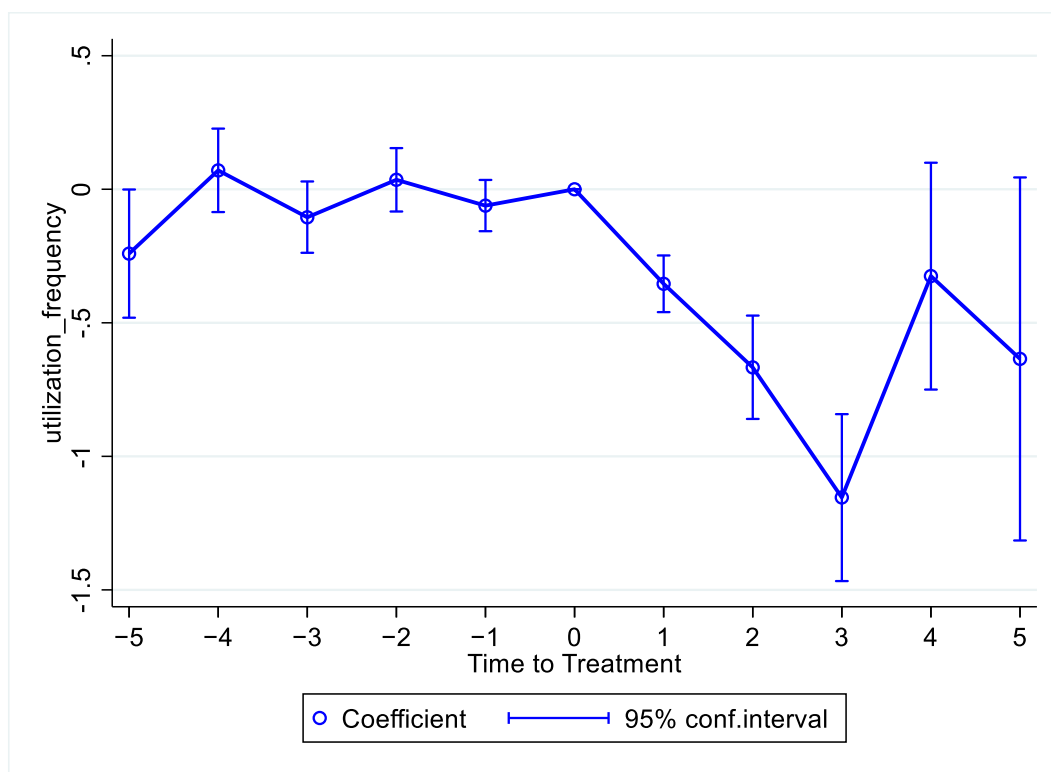


Figure 3.4 Placebo Test (Healthcare Utilization Dummy)

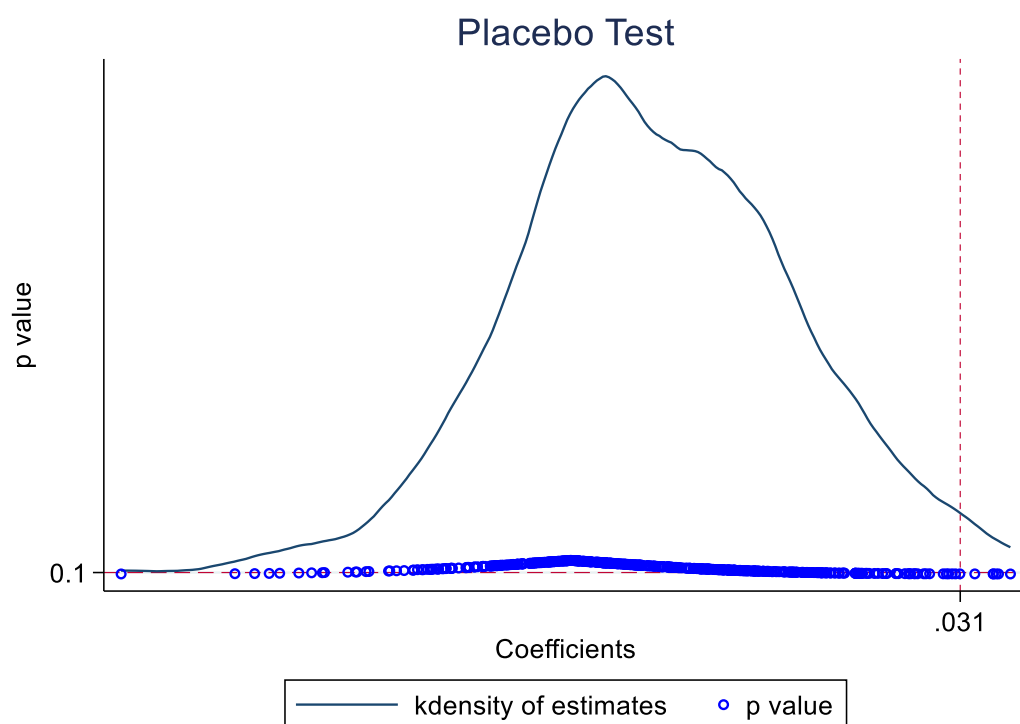
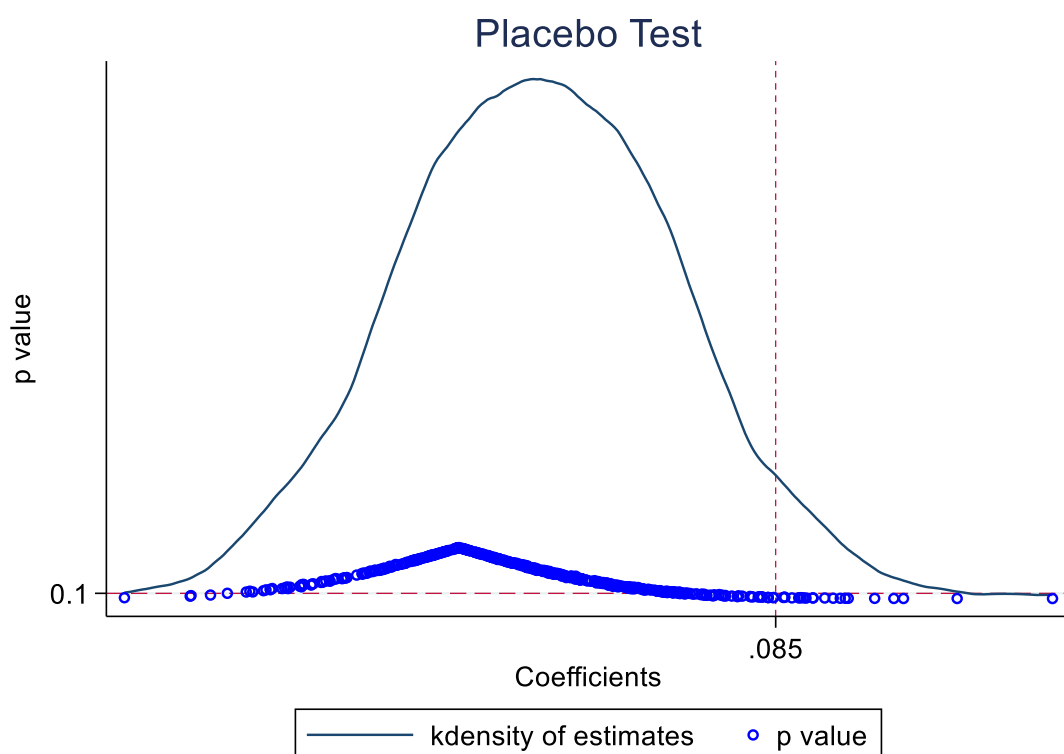


Figure 3.5 Placebo Test (Healthcare Utilization Frequency)



Chapter 3 Tables

Table 3.1 Variable Definitions

VARIABLES	Definition
Dependent variables	
healthcare_utilization	Continuous variable indicating the respondent's annual frequency of hospital visits.
utilization_dummy	Dummy variable equal to 1 if the respondent utilizes healthcare services, and 0 otherwise.
Independent Variables	
Insured	Dummy variable equal to 1 if the respondent is covered by any type of health insurance, and 0 otherwise.
Private Health Insurance	Dummy variable equal to 1 if the respondent is covered by Private Health Insurance, and 0 otherwise.
	Dummy variable equal to 1 if the respondent is covered by Public

Public Health Insurance	Health Insurance, and 0 otherwise.
URBMI	Dummy variable equal to 1 if the respondent is covered by the Urban Resident Basic Medical Insurance (URBMI), and 0 otherwise.
NRCMI	Dummy variable equal to 1 if the respondent is covered by the New Rural Cooperative Medical Insurance (NRCMI), and 0 otherwise.
URRMI	Dummy variable equal to 1 if the respondent is covered by the Urban and Rural Resident Medical Insurance (URRMI), and 0 otherwise.
Instrumental variables	
Insured_rate	Continuous variable representing the annual health insurance participation rate at the provincial level.
Private_rate	
Public_rate	
Controls	Continuous variable representing the annual public health insurance participation rate at the provincial level.
male	Dummy variable equal to 1 if the respondent is male, 0 otherwise.
age	Continuous variable indicating the respondent's age.
urban	Dummy variable equal to 1 if the respondent lives in the urban area, 0 if the respondent lives in the rural area.
Illness_occurrence	Continuous variable measuring the frequency of the respondent's illnesses in the previous month.
father_education	Continuous variables representing the highest level of education attained by the respondent's father.
mother_education	Continuous variables indicating the highest educational level achieved by the respondent's mother.
Income	Average household income of the respondent, including wages, bonuses, subsidies, dividends, pensions, minimum living allowance and so on.
Lincome	Logarithm of the average household income.

Table 3.2 Descriptive Statistics

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Dependent variables					
healthcare_utilization	43,458	1.778	2.836	0	20
utilization_dummy	43,458	0.502	0.500	0	1
Insurance variables					

Insured	43,458	0.747	0.435	0	1
public_health_insurance	43,458	0.694	0.159	0.278	0.938
private_health_insurance	43,458	0.159	0.0725	0.0165	0.543
NRCMI	43,326	0.403	0.490	0	1
URBMI	43,326	0.0750	0.263	0	1
URRMI	43,326	0.228	0.420	0	1
Instrumental variables					
insured_rate	43,458	0.740	0.151	0.363	0.952
public_insurance_rate	43,458	0.694	0.159	0.278	0.938
private_insurance_rate	43,458	0.159	0.0725	0.0165	0.543
Controls					
age	43,458	7.529	4.423	0	16
male	43,458	0.532	0.499	0	1
urban	43,458	0.411	0.492	0	1
year	43,458	2,015	3.377	2,010	2,020
father_education	43,458	3.020	1.283	1	9
mother_education	43,458	2.847	1.402	1	9
illness_occurrences	43,458	0.463	0.752	0	5
income	43,458	11,703	14,057	0	142,026
l_income	43,458	8.742	1.362	0	11.86

Note: The Chinese Yuan is the income unit of measure.

Table 3.3 Insured or not

VARIABLES	(1) Utilization_Dummy	(2) Healthcare_Utilization
insured	0.065*** (0.007)	0.222*** (0.023)
male	-	-
age	-0.029*** (0.011)	-0.100** (0.041)
urban	0.011 (0.014)	0.062 (0.047)
l_income	0.003	0.007

	(0.002)	(0.008)
illness_occurrences	0.144***	0.360***
	(0.004)	(0.010)
father_education	0.003	0.037**
	(0.004)	(0.018)
mother_education	-0.007**	-0.026*
	(0.003)	(0.015)
N	43,458	32,917

Note: The coefficients of the two-way fixed effect LPM model are displayed in column 1, while the coefficients of the two-way fixed effect Poisson model are displayed in column 2. Year dummies are also included in all models. N is the number of observations. Definitions of all variables can be found in Table 3.1. Robust standard errors are in parentheses. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

Table 3.4 Public Health Insurance and Private Health Insurance

VARIABLES	(1) Utilization_Dummy	(2) Healthcare_Utilization
public_health_insurance	0.063*** (0.007)	0.218*** (0.022)
private_health_insurance	0.023*** (0.008)	0.036 (0.026)
male	-	-
age	-0.029*** (0.011)	-0.094** (0.041)
urban	0.011 (0.014)	0.061 (0.047)
l_income	0.002 (0.002)	0.006 (0.008)
illness_occurrences	0.144*** (0.004)	0.360*** (0.010)
father_education	0.002 (0.004)	0.037** (0.018)
mother_education	-0.007** (0.003)	-0.026* (0.015)
N	43,305	32,793

F-test 13.81*** 27.96****

Note: The coefficients of the two-way fixed effect LPM model are displayed in column 1, while the coefficients of the two-way fixed effect Poisson model are displayed in column 2. Year dummies are also included in all models. N is the number of observations. The F-test is aimed to assess if the impacts of public and private health insurance on healthcare utilization are statistically different from each other. Definitions of all variables can be found in Table 3.1. Robust standard errors are in parentheses. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$

Table 3.5 DID Model Results

	(1)	(2)
VARIABLES	Utilization_Dummy	Healthcare_Utilization
Treat	0.031*** (0.009)	0.085*** (0.028)
male	-	-
age	-0.027** (0.012)	-0.085* (0.044)
urban	0.009 (0.016)	0.067 (0.050)
I_income	0.005** (0.003)	0.013 (0.008)
illness_occurrences	0.145*** (0.004)	0.364*** (0.011)
father_education	-0.001 (0.005)	0.014 (0.019)
mother_education	-0.008** (0.004)	-0.044*** (0.015)
N	35,589	26,924

Note: The coefficients of the two-way fixed effect DID regression model are displayed in column 1 and column 2. Year dummies are also included in all models. N is the number of observations. Definitions of all variables can be found in Table 3.1. Robust standard errors are in parentheses. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$

Table 3.6 Two-part Model Results (Insured or not)

VARIABLES	(1) Utilization_Dummy	(2) Healthcare_Utilization
insured	0.087*** (0.005)	0.098*** (0.021)
male	0.024*** (0.005)	-0.033 (0.034)
age	-0.032*** (0.011)	0.054 (0.038)
urban	0.011 (0.014)	0.001 (0.007)
l_income	0.003 (0.002)	0.192*** (0.009)
illness_occurrences	0.164*** (0.005)	0.013 (0.015)
father_education	0.005** (0.002)	-0.016 (0.016)
mother_education	0.005** (0.002)	0.098*** (0.021)
N	43,458	16,585

Note: The marginal effects of the CRE probit model are displayed in column 1, while the coefficients of the two-way fixed effect Poisson model are displayed in column 2. The CRE model also includes means of time-varying variables. Their coefficients are not reported for brevity, but are available upon request. Year dummies are also included in all models. N is the number of observations. Definitions of all variables can be found in Table 3.1. Standard errors are in parentheses. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

Table 3.7 Two-part Model Results (Public and Private)

VARIABLES	(1) Utilization_Dummy	(2) Healthcare_Utilization
public_health_insurance	0.083*** (0.005)	0.098*** (0.019)
private_health_insurance	0.031*** (0.006)	0.003 (0.023)
male	0.024*** (0.005)	-0.030 (0.034)
age	-0.031*** (0.011)	0.054 (0.038)
urban	0.011 (0.014)	0.001 (0.007)
l_income	0.002 (0.002)	0.193*** (0.009)
illness_occurrences	0.164*** (0.005)	0.014 (0.015)
father_education	0.005* (0.002)	-0.016 (0.016)
mother_education	0.004** (0.002)	0.098*** (0.019)
N	43,305	16,577
F-test	38.23***	9.86***

Note: The marginal effects of the CRE probit model are displayed in column 1, while the coefficients of the two-way fixed effect Poisson model are displayed in column 2. The CRE model also includes means of time-varying variables. Their coefficients are not reported for brevity, but are available upon request. Year dummies are also included in all models. N is the number of observations. The F-test is aimed to assess if the impacts of public and private health insurance on healthcare utilization are statistically different from each other. Definitions of all variables can be found in Table 3.1. Standard errors are in parentheses. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

Table 3.8 Control Function Approach (Insured or not)

VARIABLES	(1) Utilization Dummy	(2) Healthcare Utilization
insured	0.077*** (0.006)	0.217*** (0.023)
residual	0.125*** (0.010)	0.110*** (0.042)
male	0.021*** (0.005)	-
age	-0.026** (0.011)	-0.092** (0.041)
urban	0.002 (0.014)	0.056 (0.047)
l_income	0.000 (0.002)	0.004 (0.008)
illness_occurrences	0.164*** (0.005)	0.359*** (0.010)
father_education	0.002 (0.002)	0.035** (0.018)
mother_education	0.001 (0.002)	-0.029* (0.015)
N	43,297	32,826
Test for residual (Chi2 Statistic)	169.45	6.94
P-value	0.0000	0.0085

Note: The marginal effects of the CRE probit model are displayed in column 1, while the coefficients of the two-way fixed effect Poisson model are displayed in column 2. The CRE model also includes means of time-varying variables. Their coefficients are not reported for brevity, but are available upon request. Year dummies are also included in all models. N is the number of observations. Definitions of all variables can be found in Table 3.1. Robust standard errors are in parentheses. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

Table 3.9 Control Function Approach (Public and Private)

VARIABLES	(1) Utilization_Dummy	(2) Heathcare_Utilizati
public_insurance	0.071*** (0.005)	0.212*** (0.022)
private_insurance	0.031*** (0.006)	0.035 (0.026)
residual_public	0.099*** (0.008)	0.063* (0.036)
residual_private	0.019* (0.010)	0.039 (0.055)
male	0.021*** (0.005)	-
age	-0.026** (0.011)	-0.092** (0.041)
urban	0.003 (0.015)	0.056 (0.047)
l_income	-0.000 (0.002)	0.003 (0.008)
illness_occurrences	0.164*** (0.005)	0.359*** (0.010)
father_education	0.002 (0.003)	0.033* (0.018)
mother_education	0.002 (0.002)	-0.030** (0.015)
N	43,305	32,832
Test for public_residual(Chi2 Statistic)	139.49	3.04
P-value	0.0000	0.0813
Test for private_residual(Chi2 Statistic)	3.17	0.52
P-value	0.0749	0.4688

Note: The marginal effect of the CRE probit model is displayed in column 1, while the coefficients of the two-way fixed effect Poisson model are displayed in column 2. The CRE model also includes means of time-varying variables. Their coefficients are not reported for brevity, but are available upon request. Year dummies are also included in all models. N is the number of observations. Definitions of all variables can be found in Table 3.1. Standard errors are in parentheses. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

Table 3.10 Healthcare Utilization Inequalities for insured and uninsured Children

	Group Variable	Group	Concentration Index (CI)	Difference	N
(1)	Insured	Insured = 0	0.020*** (0.004)	-0.013*** (0.005)	11,015
		Insured = 1	0.007*** (0.002)		32,282
(2)	Insured=1	Treat = 0	0.021*** (0.003)	-0.055*** (0.006)	21,323
		Treat = 1	-0.035*** (0.005)		9,863
(3)	Insured=1	Urban = 0	0.017*** (0.003)	-0.023*** (0.005)	18,692
		Urban = 1	-0.006 (0.004)		13,590
(4)	Insured=1	High_GRP = 0	0.014*** (0.003)	-0.018*** (0.005)	17,329
		High_GRP = 1	-0.004 (0.004)		14,953
(5)	Total CI	N = 43,297	0.014*** (0.002)		

Note: CI is calculated based on demand-standardized healthcare utilization. Treat is a dummy variable equal to 1 if an individual is covered under the merged URRMI policy and 0 otherwise. N is the number of observations. Robust standard errors are in parentheses. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

Appendix for Chapter 3

Table A3.11 First Stage: Control Function Approach (Insured or not)

VARIABLES	(1)
	Insured
Insured_rate	0.857*** (0.026)
male	0.007 (0.004)
age	-0.009 (0.012)
urban	0.016 (0.013)
l_income	0.005** (0.002)
illness_occurrences	0.000 (0.003)
father_education	0.006*** (0.002)
mother_education	0.008*** (0.002)
N	43,297

Note: The marginal effect of the CRE probit model is displayed in column 1. The CRE model also includes means of time-varying variables. Their coefficients are not reported for brevity, but are available upon request. N is the number of observations. Robust Standard errors are in parentheses. Definitions of all variables can be found in Table 3.1. *** p<0.01, ** p<0.05, * p<0.1

Table A3.12 First Stage: Control Function Approach (Public and Private)

VARIABLES	(1)	(2)
	Public health	Private health

public_rate	0.909*** (0.024)	
private_rate		0.669*** (0.028)
male	0.006 (0.004)	0.012*** (0.004)
age	-0.016 (0.012)	0.014 (0.009)
urban	0.014 (0.013)	0.012 (0.010)
l_income	0.005** (0.002)	0.004** (0.002)
illness_occurrences	-0.002 (0.003)	0.004 (0.003)
father_education	0.004 (0.002)	0.014*** (0.002)
mother_education	0.005** (0.002)	0.012*** (0.002)
Observations	43,305	43,305

Note: The marginal effect of the CRE probit model is displayed in column 1. The CRE model also includes means of time-varying variables. Their coefficients are not reported for brevity, but are available upon request. N is the number of observations. Robust Standard errors are in parentheses. Definitions of all variables can be found in Table 3.1. *** p<0.01, ** p<0.05, * p<0.1

Due to the potential overlap between public and private health insurance, we categorized the variables into three groups: individuals covered only by public health insurance (only_public), only by private health insurance (only_private), and by both public and private health insurance (public_private), to ensure the robustness of our results. Table A3.13 presents the findings. In Column (1), the coefficient associated with public health insurance is statistically significant and equal to 0.066, indicating that having public health insurance is associated with a 6.6 percentage point higher

probability of utilizing healthcare services. The coefficient associated with private health insurance is statistically significant and equal to 0.042, indicating a 4.2 percentage point increase in the likelihood of healthcare utilization. For individuals covered by both public and private health insurance, the coefficient is 0.083, reflecting an 8.3 percentage point higher probability of utilizing healthcare services. F-tests indicate a significant difference between the effects of private and combined insurance, while the difference between public and combined insurance is marginally significant.

In Column (2), the coefficient for public health insurance is statistically significant and equal to 0.231, indicating that having public health insurance is associated with a 23.1 percentage point increase in the frequency of healthcare utilization. The coefficient for private health insurance is 0.108. For individuals covered by both public and private health insurance, the coefficient is 0.247, indicating a 24.7 percentage point increase in the frequency of healthcare utilization. F-tests show a significant difference between the effects of public and private insurance and between private and combined insurance, but no significant difference is observed between public and combined insurance.

These findings indicate that public health insurance plays a stronger role in promoting both the probability and frequency of healthcare utilization compared to private health insurance. Combined coverage has the greatest impact, likely due to the complementary effects of both types of insurance, further underscoring the importance of public health insurance in improving healthcare access and utilization.

Table A3.13 Only Public Health Insurance and Only Private Health Insurance

	(1)	(2)
VARIABLES	Utilization_Dummy	Healthcare_Utilization
only_public	0.066*** (0.007)	0.231*** (0.023)
only_private	0.042*** (0.016)	0.108* (0.055)
public_private	0.083*** (0.010)	0.247*** (0.033)
male	-	-
age	-0.029*** (0.011)	-0.094** (0.041)
urban	0.011 (0.014)	0.061 (0.047)
l_income	0.002 (0.002)	0.006 (0.008)
illness_occurrences	0.144*** (0.004)	0.360*** (0.010)
father_education	0.002 (0.004)	0.037** (0.018)
mother_education	-0.007** (0.003)	-0.026* (0.015)
N	43,296	32,825
F-test (only_public =only private)	2.53	5.33**
F-test (only_public	3.47*	0.36

=public_ private)

F-test (only_private 6.37**

6.34**

=public_ private)

Note: The coefficients of the two-way fixed effect LPM model are displayed in column 1, while the coefficients of the two-way fixed effect Poisson model are displayed in column 2. Year dummies are also included in all models. Only_public refers to being covered exclusively by public health insurance. Only_private refers to being covered exclusively by private health insurance. Public_private refers to being covered by both public and private health insurance. Definitions of other variables can be found in Table 3.1. N is the number of observations. Robust standard errors are in parentheses. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

Table A3.14 compares the impact of public and private health insurance on healthcare utilization among insured individuals to the results in Table 3.4, which includes all children regardless of insurance status. By focusing exclusively on insured individuals, this analysis reduces potential bias introduced by the distinct characteristics of uninsured children and allows for a more direct comparison of insurance type effects. In Column (1) of both tables, the coefficient for public health insurance remains statistically significant, indicating that having public health insurance is associated with a higher probability of healthcare utilization. Specifically, the coefficient is equal to 0.047 in Table A3.14, indicating a 4.7 percentage point increase in the likelihood of utilization, compared to 0.063 in Table 3.4, which reflects a 6.3 percentage point increase. Similarly, private health insurance has a statistically significant but smaller effect in both tables, with the coefficient decreasing from 0.023 in Table 3 to 0.020 in Table A3.14, reflecting a 2.0 percentage point increase. Importantly, the F-test in both cases confirms a significant difference between the effects of public and private health insurance, emphasizing the stronger role of public health insurance in promoting healthcare utilization. In Column (2), the coefficient for public health insurance remains statistically

significant in both tables, though its magnitude decreases from 0.218 in Table 3.4 to 0.158 in Table A3.14, which reflects a 15.8 percentage point increase. This reduction suggests that the inclusion of uninsured individuals in Table 3.4 amplifies the observed effect of public health insurance. For private health insurance, the effect remains insignificant in both models, although the coefficient is slightly larger in Table A3.14 (0.043) compared to Table 3.4. The F-tests consistently show that public health insurance has a significantly greater impact on the frequency of healthcare utilization than private health insurance in both subsamples. These differences and similarities confirm the robustness of the findings. By isolating insured individuals, Table A3.14 provides additional evidence supporting the reliability of the results and highlights the prominent role of public health insurance in increasing both the likelihood and frequency of healthcare utilization.

Table A3.14 Public Health Insurance and Private Health Insurance (Insured)

	(1)	(2)
VARIABLES	Utilization_Dummy	Healthcare_Utilization
public_health_insurance	0.047*** (0.018)	0.158*** (0.059)
private_health_insurance	0.020** (0.010)	0.043 (0.028)
male	-	-
age	-0.031** (0.014)	-0.094** (0.041)

urban	0.010 (0.018)	-0.061 (0.048)
l_income	0.004 (0.003)	0.083 (0.055)
illness_occurrences	0.143*** (0.004)	0.009 (0.009)
father_education	-0.003 (0.005)	0.359*** (0.012)
mother_education	-0.007* (0.004)	0.005 (0.021)
N	32,284	22,958
F-test	2.71*	4.07**

Note: The coefficients of the two-way fixed effect LPM model are displayed in column 1, while the coefficients of the two-way fixed effect Poisson model are displayed in column 2. Year dummies are also included in all models. N is the number of observations. The F-test is aimed to assess if the impacts of public and private health insurance on healthcare utilization are statistically different from each other. Definitions of all variables can be found in Table 3.1. Robust standard errors are in parentheses. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

Table A3.15 presents the results of Equation (3-1). Column 1 reports the results for the healthcare utilization dummy using a two-way fixed effects linear probability model. Column 2 reports the results for healthcare utilization frequency using a two-way fixed effects negative binomial model. In Column (1), the coefficient for being insured is 0.065 ($P < 0.01$), indicating that being insured is associated with a 6.5 percentage point higher probability of using healthcare services. In Column (2), the IRR of being insured is 1.316 ($P < 0.01$), which indicates that being insured is associated with a 31.6 percent increase in the frequency of healthcare utilization. This is consistent with our baseline model results in Table 3.3.

Table A3.15 Insured or not (Negative Binomial Model)

	(1)	(2)
VARIABLES	Utilization Dummy	Healthcare Utilization
insured	0.065*** (0.007)	1.326*** (0.026)
male	-	1.099*** (0.040)
age	-0.029*** (0.011)	0.945*** (0.004)
urban	0.011 (0.014)	1.200*** (0.035)
l_income	0.003 (0.002)	1.031*** (0.007)
illness_occurrences	0.144*** (0.004)	1.484*** (0.012)
father_education	0.003 (0.004)	1.072*** (0.013)
mother_education	-0.007** (0.003)	1.003 (0.010)
N	43,458	32,917

Note: The coefficients of the two-way fixed effect LPM model are displayed in column 1, while the IRRs of the two-way fixed effect negative binomial model are displayed in column 2. Coefficients of the negative binomial model are not reported for brevity, but are available upon request. Year dummies are also included in all models. N is the number of observations. Definitions of all variables can be found in Table 1. Standard errors are in parentheses. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

Table A3.16 shows the estimates of Equation (3-2), which examines the effect of public and private health insurance on healthcare utilization. Column 1 presents the coefficients of the two-way fixed effect linear probability model in the case in which the dependent variable is the healthcare utilization dummy. Column 2 displays the Incidence

Rate Ratios (IRRs) calculated using the two-way fixed effects negative binomial model for the case in which the dependent variable is healthcare utilization frequency. In Column (1), the coefficient associated with public health insurance is statistically significant and equal to 0.063, indicating that having public health insurance is associated with a 6.3 percentage point higher probability of utilizing healthcare services. By contrast, having private health insurance is associated with a 2.3 percentage point higher probability of using healthcare services. In Column (2), the IRR for public health insurance is statistically significant and equal to 1.303, which indicates that having public health insurance is associated with a 30.3 percent increase in the frequency of healthcare utilization. By contrast, having private health insurance is associated with a 7.7 percent higher frequency of healthcare utilization. This implies that children covered by public health insurance are more likely to use healthcare services compared to those with private health insurance and is consistent with our Hypothesis 2.

Table 3.16 Public health insurance and private health insurance (Negative Binomial Model)

	(1)	(2)
VARIABLES	Utilization_Dummy	Healthcare_Utilization
public_health_insurance	0.063*** (0.007)	1.310*** (0.025)
private_health_insurance	0.023*** (0.008)	1.082*** (0.024)
male	-	1.101*** (0.040)
age	-0.029*** (0.011)	0.945*** (0.004)

urban	0.011 (0.014)	1.200*** (0.035)
l_income	0.002 (0.002)	1.030*** (0.007)
illness_occurrences	0.144*** (0.004)	1.484*** (0.012)
father_education	0.002 (0.004)	1.072*** (0.013)
mother_education	-0.007** (0.003)	1.002 (0.010)
N	43,305	32,832

Note: The coefficients of the two-way fixed effect LPM model are displayed in column 1, while the IRRs of the two-way fixed effect negative binomial model are displayed in column 2. Coefficients of the negative binomial model are not reported for brevity, but are available upon request. Year dummies are also included in all models. N is the number of observations. Definitions of all variables can be found in Table 1. Standard errors are in parentheses. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

Chapter 4 Sleep and Medical Expenditure

4.1 Introduction

In response to rapid advancements in Internet technology and economic growth, China's night-time economy has undergone a substantial transformation.²² The nighttime economy has expanded the options available for people to engage in consumption and entertainment during the night, through activities such as live streaming on online shopping platforms and the growth of offline nighttime cultural and entertainment venues. The surge in economic activity boosts the nation's economy, yet it also brings several potential adverse effects, such as a substantial influence on individuals' sleep patterns. Due to the growth in nighttime activities, bedtime gradually shifts to later hours, resulting in a reduction in the duration of sleep.²³

In addition, the prevalence of sleep disorders is more pronounced in the middle-aged and elderly, who are also particularly vulnerable to the adverse health consequences linked to inadequate and poor sleep.²⁴ The heightened vulnerability to sleep issues in middle-aged and older adults stresses the vital importance of sleep for their health and well-being, emphasizing the necessity for targeted research within this age group.

²² According to Lin et al. (2022), the Night Time Economy (NTE) incorporates a wide range of online and offline economic activities occurring from 6 pm to 6 am, such as night markets, shopping malls, live e-commerce streaming, etc. In recent years, China's nighttime economy has experienced significant growth due to the implementation of various policies by provincial and municipal governments aimed at fostering it.

²³ Chinese Sleep Research Report (2022) indicates that over the past decade, the average sleep duration of the Chinese population has diminished by approximately 1.44 hours.

²⁴ Gulia and Kumar (2018) argue that the elderly are more prone to sleep disorders because their circadian rhythm mechanisms are less efficient, and several diseases commonly observed in older individuals, such as diabetes and hypertension, are also associated with sleep disturbances.

Furthermore, a decrease in both the duration and quality of sleep can have significant economic consequences. Several studies have examined the economic implications of sleep deprivation, which include diminished work efficiency, higher mortality rates (Cappuccio et al., 2010), and increased likelihood of traffic accidents (Philip et al., 2014). While these studies focus on the broader economic costs of sleep deprivation, they overlook its impact on individual medical expenses. The objective of our study is to investigate the specific influence of sleep on medical expenses among middle-aged and older individuals. Middle-aged and elderly individuals constitute a significant portion of healthcare service users. Minimizing medical expenses for this group is crucial for reducing the economic burden on society and improving public health. Lowering healthcare expenses for the middle-aged and elderly will not only increase their disposable income but will also facilitate more efficient distribution of healthcare resources and diminish the overall strain on the healthcare system. Hence, the object of our study is to conduct a comprehensive examination of the impact of sleep duration and sleep quality on medical expenditures among middle-aged and elderly Chinese people. By doing so, we aim to increase public awareness regarding the significance of sleep.

Specifically, our research addresses the following questions. First, we assess the relationship between night-time sleep duration and out-of-pocket OOP medical expenditures/catastrophic health expenditures (CHE) ²⁵among middle-aged and older

²⁵ Catastrophic Health Expenditure (CHE) occurs when a respondent's out-of-pocket medical expenses exceed 40% of their household's capacity to pay (CTP). The capacity to pay is determined by subtracting food expenditure from total household expenditure (Xu et al., 2003).

adults. Second, we analyze the impact of sleep quality on the same variables. Finally, we investigate mediating factors that link sleep duration and quality with out-of-pocket (OOP) medical expenditure and catastrophic health expenditure (CHE), with a particular focus on how the frequency of outpatient visits and hospitalizations influences this relationship. To this end, we use data from the 2011 to 2018 wave of the China Health and Retirement Longitudinal Study (CHARLS), which covers respondents aged 45 and over from 28 provinces across China.

To the best of our knowledge, we are the first to discuss the relationship between sleep and Out-of-Pocket medical expenditures in the context of China. Jasani et al. (2020) identify that both shorter and longer sleep durations are associated with higher annual healthcare costs in the US from 2010 to 2011. Discussing this issue within the Chinese context is crucial, especially considering the rapidly decreased sleep duration²⁶ and the relatively low health insurance reimbursement rates²⁷ in China.

Secondly, the existing literature on sleep duration often uses inconsistent categorization standards and faces selection biases. Notably, Itani et al. (2017) point out the varying definitions of short sleep across studies, with some marking it as less than five hours and others as less than six. To address these gaps, our study analyses sleep duration as a continuous variable, offering a broader perspective than fixed categories. Additionally, we apply Propensity Score Matching (PSM) to effectively control for selection biases, a

²⁶ Based on Zhu (2023), the average sleep time for Chinese adults drop from 8.2 hours to 7.6 hours from 2010 to 2016. Additionally, the percentage of individuals sleeping less than 7 hours rise sharply from 11.8% in 2010 to 24.1% in 2016.

²⁷ According to the World Health Organization (2015), despite the rise in reimbursement rates in China over time, they are still low in both urban and rural regions. About 64% of inpatient expenditures are covered by health insurance for elderly individuals in urban, compared to 53% in rural regions.

method not widely used in segmented sleep duration research. This approach aims to provide a clearer understanding of sleep duration's effects.

Finally, to the best of our knowledge, no literature has looked at the impact of sleep on Catastrophic Health Expenditure (CHE). We fill this gap by analyzing the effects of both sleep duration and sleep quality on CHE. Examining catastrophic health expenditure (CHE) is crucial because it provides valuable insights into the financial burden healthcare costs can place on individuals and households. Xu et al. (2007) argue that CHE is a key indicator for assessing the equity of a healthcare system, revealing how medical expenses can lead to financial hardship for families. Thus, examining CHE is crucial for informing policies aimed at reducing the financial impact of healthcare on individuals and households.

Our baseline model demonstrates a U-shaped relationship between sleep duration and out-of-pocket (OOP) medical expenditure. Moreover, a negative association is observed between sleep duration and CHE. Our Propensity Score Matching (PSM) results further indicate that sleeping less than 6 hours is linked to increased OOP costs and a greater probability of experiencing CHE. Additionally, better sleep quality is associated with lower OOP medical expenditure and a reduced risk of incurring CHE. Finally, our analysis reveals that the frequency of outpatient visits and hospitalizations serve as mediating variables in the relationship between sleep duration/sleep quality and OOP/CHE. Notably, the frequency of outpatient visits has a more substantial mediating effect.

The remaining part of the paper is structured as follows. Section 4.2 provides a comprehensive analysis of the existing literature with a focus on the gaps that our study

aims to fill. Section 4.3 introduces our baseline specifications and estimation methods. Section 4.4 introduces the data we use and provides descriptive statistics. Section 4.5 presents and discusses our empirical findings. Section 6 concludes and discusses the policy implications of our findings, as well as directions for future research.

4.2. Literature Review

4.2.1 Sleep Duration

To our knowledge, only one paper, namely Jasani et al. (2020), discusses the relationship between sleep duration and healthcare expenditure. The authors examine the influence of short sleep duration (less than 7 hours per day) or long sleep duration (more than 8 hours per day) on healthcare expenditure in the United States from 2010 to 2011. The purpose of this study is to determine which types of sleep durations are linked to lower healthcare costs. The authors make use of a cross-sectional data set made up of 6,476 respondents drawn from the nationally representative Medical Expenditure Panel Survey (MEPS). The results reveal that, compared to the average sleep duration, both short and long sleep duration are associated with higher annual healthcare costs. In addition, the authors show that among individuals with chronic disease, those with sleep deprivation have the greatest medical expenses. This suggests that sleep deprivation is detrimental to health, especially for individuals who already suffer from chronic disease. Overall, the results in this paper imply that optimal sleep duration (greater than 7 hours, less than 8 hours) is beneficial to minimizing healthcare costs. Yet, even though the perspective of this paper is novel, the paper suffers from a significant limitation: the cross-sectional nature of the data prevents in fact the authors from determining causal relationships between sleep duration and healthcare costs. Moreover, this paper only

examines the effect of sleep duration on healthcare expenditures, neglecting the effects of sleep quality. Finally, short (less than 7 hours) and long (more than 8 hours) sleep duration categories are artificial and oversimplify sleep continuity and individual differences. This artificial categorization can lead to ambiguity at the boundaries, where individuals are classified into different categories based on small differences in sleep duration.

Hillman et al. (2018) explore the relationship between inadequate sleep and economic burden in Australia from 2016 to 2017, considering both the direct costs related to sleep disorders and the indirect costs linked to conditions attributable to poor sleep. Excessive Daytime Sleepiness (EDS) is used to measure inadequate sleep. The majority of the data used in this study comes from the 2016 Sleep Health Foundation national survey, with additional information coming from published research articles and a government database. The researchers utilize a combination of an economic model, a systematic analysis, and a cost-of-illness approach to explore loss of productivity, cost of illness, and additional societal costs, arising from insufficient sleep. Their results show that inadequate sleep has a significant economic impact, including reduced productivity, increased cost of illness, and higher mortality rates. The authors conclude that inadequate sleep has economic costs of tens of billions of dollars annually. Although this paper examines the costs of sleep deprivation from a variety of perspectives, the period studied is only one year, which may not adequately reflect the costs of sleep deprivation over time. Furthermore, the measurement of sleep deprivation using EDS is subjective,

and in general, in addition to night-time sleep, each individual's daytime activity level and tolerance influence daytime sleepiness.

Stepptoe et al. (2006) conduct a study about the relationship between sleep duration and health in young adults between 1999 and 2001. The data in their study comes from an anonymous questionnaire and includes a sample of 17,465 individuals aged 18 to 30 from 24 different countries. According to the results of the survey, more than 60 percent of young adults sleep between seven to eight hours, and more than 20 percent of young people get less than 6 hours of sleep. The results show that short sleep duration (less than six hours) is highly associated with poor self-rated health conditions. However, the authors do not find any association between long sleep duration (more than 10 hours) and poor self-reported health. This finding contradicts previous research, which finds that both short and long-sleepers have worse health outcomes. This could be because young people typically sleep longer than older people. Although the findings of this study are intriguing, there are some limitations. Because the data are cross-sectional, causality cannot be determined. Second, the representativeness of the results may be compromised by the fact that college students reside in a relatively healthy environment and, consequently, have a relatively good health status. Lastly, self-rated health is selected as the measure of health, which may not be accurate due to different evaluation criteria used by different individuals.

Aneni et al. (2023) investigate the relationship between sleep duration and cardiovascular health, as well as related healthcare expenditures and usage among working individuals. The data for this study come from the Baptist Health South Florida (BHSF) Health Risk Assessment, which is voluntarily administered to 8629 adult employees in 2014. Three categories of sleep duration are considered: less than 6 hours, 6 to 9 hours, and more than 9 hours. The results suggest that individuals sleeping between 6 and 9 hours are nearly twice as likely to enjoy improved cardiovascular health compared to those who sleep less than 6 hours. Moreover, those who sleep longer than 9 hours have a threefold greater chance of achieving improved cardiovascular results. In addition, the results indicate that employees who sleep for more than six hours have lower medical costs than those who sleep for less than six hours. These findings suggest that adequate sleep duration is essential for cardiovascular health and beneficial for reducing medical expenses. Nonetheless, this paper suffers from a number of limitations. First, the study is conducted among working adults, so the sample may not be representative. Second, as the data covers only the year 2014 and is cross-sectional, it prevents the assessment of long-term trends and cause-and-effect dynamics. Thirdly, the artificial classifications of short-, medium-, and long-term sleep categories oversimplifies the continuum and individual variations in sleep. Lastly, this study examines only the impact of sleep duration on cardiovascular disease, ignoring the potential influence on other illnesses and the interplay between different diseases.

Devine and Wolf (2016) explore the effects of night-time sleep and naps on physical and mental health in the US. This study collects data from 313 individuals aged from 34 to 82. Two-thirds of the participants report napping. According to the study's findings,

people who report napping have higher levels of inflammatory markers, a larger waist-to-hip ratio, and more overall medical issues than people who do not report napping. On the basis of cluster analysis, nappers are further divided into three categories: sleep 5 hours per night and nap two to three times per week, sleep 6 hours per night and nap four to five times per week, and sleep 6.5 hours per night and naps less than twice per week. The results show that participants who report frequent napping combined with an average 5-hour night-time sleep duration show poor health conditions. By contrast, health outcomes are more favourable for participants who sleep longer at night and nap infrequently. Unlike other papers, this paper considers different sleep patterns and includes naps. However, there are some limitations in this paper. Firstly, the cross-sectional nature of the data makes it impossible to infer the causal relationship between sleep and health outcomes. Secondly, this study is limited in its generalizability and reliability by the relatively small size of the sample (just over 300 people). Another problem is the small difference in night-time sleep between the three groups considered. These small differences may make the observed effects and associations less meaningful.

4.2.2 Sleep Quality

Zhang et al. (2016) examine the correlation between sleep quality and the utilization of healthcare services in Dongguan, China. Sleep quality is evaluated using the Chinese version of the Pittsburgh Sleep Quality Index (PSQI). The PSQI questionnaire consists of 19 questions, the higher the score, the lower the quality of sleep. Utilization of health services is measured by physician visits every two weeks and hospitalizations each year.

The data come from a cross-sectional health survey conducted in Dongguan City, Guangdong Province. The sample consists of 4,067 people older than 15. According to the results, poor sleep quality is significantly associated with frequent healthcare utilization, including visits to the doctor every two weeks and annual hospitalization. The findings of this study suggest that enhancing sleep quality can reduce health service utilization. This paper has some limitations. First, the data are collected from a single city in China, which may influence the representativeness of the results. Furthermore, as this is a cross-sectional study, it is impossible to determine the causal relationship between sleep quality and healthcare utilization.

João (2018) conduct a cross-sectional study in 2018 to investigate the influence of sleep quality on mental health in non-clinical adults. This cross-sectional study collect data from 1576 adults from Portugal, Brazil, and Spain. The sleep quality is also assessed by the PSQI (Pittsburgh Sleep Quality Index), including 19 questions. To evaluate mental health parameters, such as depression, anxiety, and stress, this study utilizes the Depression Anxiety Stress Scale (DASS-21). Results indicate a significant correlation between good sleep quality and the lower levels of depression, anxiety, and stress among the participants, highlighting the importance of sleep quality in maintaining mental health. This study faces certain constraints. To begin with, the sources of the data are Portugal, Brazil, and Spain. Each of these countries has its own unique lifestyle, social norms, and health behaviors, which can significantly impact factors such as sleep patterns and the perception of mental health. These distinctions may impact sleep patterns, responses to surveys, and perceptions of mental health. The diversity of culture in question has the potential to impact the comparability and consistency of the data

across these countries. Secondly, the study's design is cross-sectional, which inherently limits its capacity to establish causality.

4.2.3 Sleep Duration and Sleep Quality

Pilcher et al.(1997) conduct experiments to investigate the influence of sleep duration and sleep quality on health, well-being, and fatigue among college students in the US. The Cornell Medical Index (CMI) is applied to assess physical health. The Pittsburgh Sleep Quality Index (PSQI) is used to measure sleep quality. The authors conduct two experiments with volunteers from a university. The first experiment used 30 volunteers completing all the questionnaires near the end of the exam period. The second experiment was conducted at the beginning of the semester, with 87 students participating. Both experiments clearly show that sleep quality is more strongly related to health, well-being, and sleepiness than sleep duration. Poorer sleep quality is linked to more physical health issues, psychological issues, and drowsiness, and this correlation is not influenced by sleep duration. This paper implies that the quality of our sleep is more important to our health than the duration of sleep. In addition, as the correlation between sleep duration and sleep quality is weak, increasing sleep duration does not necessarily enhance sleep quality. This paper has some limitations. Firstly, the study is based on students at a single university, thereby restricting the extent to which the findings can be applied to a broader population. Furthermore, the first experiment consists of a mere 30 volunteers, a sample size that may not be sufficient to yield robust

statistical findings. Despite the inclusion of 87 students in the second experiment, this sample size may still be inadequate. Ultimately, the two experiments are carried out after the completion of the final exams and at the commencement of the new semester. This could have resulted in a time-related bias, as the psychological states of students may have varied considerably at these two points in time. Finally, due to the correlational design of the investigation, causality can not be determined.

4.2.4 Contribution

Our paper is the first to discuss the relationship between sleep and out-of-pocket healthcare expenditures in the context of China. Discussing this issue within the Chinese context is crucial, especially considering the relatively low health insurance reimbursement rates in China and the rapid development of the country's nighttime economy. In addition, with the exception of Jasani et al. (2020), most studies have focused solely on the health benefits of sleep, disregarding its impact on medical expenditures. While traditional sleep studies emphasize its biological importance, examining sleep in the context of medical expenditures highlights its economic significance. Analyzing the links between sleep and medical expenditures can help policymakers evaluate the cost-effectiveness of sleep-related policies. Additionally, it is beneficial for individuals to understand the economic value of sleep.

Existing literature often segments sleep duration with inconsistent standards and struggles with selection biases.²⁸ We add to this literature by initially analysing sleep duration as a continuous variable. This can provide a better understanding than studies with rigid sleep duration categories. Further, we employ Propensity Score Matching (PSM) to rigorously control for selection biases, a method not commonly combined with segmented sleep analysis in existing research. We utilize Propensity Score Matching (PSM) in segmented sleep to mitigate potential selection biases by matching individuals with comparable characteristics (health-rated issues, socioeconomic status, etc.). This ensures a more accurate estimation of the relationship between segmented sleep and medical costs.

Finally, to the best of our knowledge, no literature has analyzed the impact of sleep duration/quality on Catastrophic Health Expenditure(CHE). We believe it is important to focus on CHE, as, especially in the Chinese context, CHE can have a huge influence on families, frequently resulting in substantial economic hardship.

4.3. Hypotheses

Previous research concludes that individuals who sleep insufficiently or excessively experience negative consequences. Jasani et al. (2020) argue that both short (<7 hours) and long (>8 hours) sleep durations are associated with higher healthcare costs in the

²⁸ Aneni et al. (2023) define short sleep durations as less than 6 hours and long sleep durations as more than 9 hours. In contrast, Jasani et al. (2020) categorize sleep duration as short sleep when it is less than 7 hours and as long sleep when it exceeds 8 hours. Steptoe et al. (2006) characterize short sleep as lasting less than 6 hours, and long sleep as more than 10 hours. Additionally, Itani et al. (2017) underscore in their systematic review the disparities in defining short sleep among different studies, with some defining it as less than five hours and others as less than six.

United States. Aneni et al. (2023) reveal that people with less than 6 hours of sleep and more than 9 hours of sleep are at higher risk of cardiovascular disease. Cappuccio et al. (2010) conduct a systematic review and conclude that both longer and shorter sleep periods are related to an increased risk of mortality. By examining the relationship between sleep duration and out-of-pocket medical expenses, we aim to identify the optimal amount of sleep that minimizes healthcare costs for individuals. We hypothesize that both insufficient sleep and excessive sleep are associated with increased healthcare expenditures. Based on these considerations, we propose the following hypothesis:

Hypothesis 1a: There is a U-shaped relationship between sleep duration and individual out-of-pocket healthcare expenditures.

Hypothesis 1b: There is a U-shaped relationship between sleep duration and Catastrophic health expenditure(CHE).

In addition to focusing on sleep duration, we must also consider sleep quality, which is an essential factor of sleep. Zhang et al. (2016) argue that there is a significant link between poor sleep quality and frequent utilization of medical services in Dongguan, China. Pilcher et al.(1996) also observe that poorer sleep quality is strongly linked to worse physical health conditions, lower well-being, and sleepiness. So, we propose the second hypothesis.

Hypothesis 2a: Better sleep quality is associated with lower out-of-pocket (OOP) medical expenses.

Hypothesis 2b: Better sleep quality is associated with a lower probability of incurring Catastrophic Health Expenditure (CHE).

4.4 Specifications and Methodology

4.4.1 Baseline Model

4.4.1.1 Sleep Duration

4.4.1.1.1 Continuous Sleep Duration

To test Hypotheses 1a and 1b, we estimate the relationship between sleep duration and OOP medical expenditure/CHE. Based on previous research, we propose that the relationship between sleep duration and out-of-pocket expenditures/CHE may not be a simple linear one, as both too long and too short sleep durations may have negative consequences that result in increased out-of-pocket health care expenditures (Jasani et al., 2020). These relationships can be explained by introducing a quadratic term for nighttime sleep duration. Based on Draper and Smith (1998) and Stimson et al. (1978), we estimate the following models:

$$L_OOP_Medical_Expenditure_{it}/Catastrophic_Health_Expenditure_{it} = \beta_1 * Night_Sleep_Duration_{it} + \beta_2 * Night_Sleep_Duration_sq_{it} + \beta_3 X_{it} + u_i + v_t + \varepsilon_{it} \quad (4-1)$$

$L_OOP_Medical_Expenditure_{it}$ is a continuous variable that represents the logarithm of out-of-pocket medical expenditures for individual i at wave t .

$Catastrophic_Health_Expenditure_{it}$ is a dummy variable with a value of 1 if respondent i incurs catastrophic health expenditure at wave t and 0 otherwise.

$Night_Sleep_Duration_{it}$: is a continuous variable indicating the time spent sleeping at night for individual i at wave t .

Night_Sleep_Duration_sq_{it}: is a continuous variable that represents the square of the nighttime sleep duration of individual *i* at wave *t*.

The control variables (X_{it}) include:

Male_{it}, which is a dummy variable equal to 1 for males, and 0 otherwise. The coefficient associated with this variable is expected to be negative. According to Bertakis et al.(2000), women's average expenses for primary care, specialist care, emergency care, diagnostic services, and overall annual costs are much greater than men's. Owens (2008) also indicates that there is a tendency for women to show higher utilization rates of healthcare services and allocate greater financial resources towards healthcare expenditures in comparison to males.

Age_{it} is the age of the individual *i* at time *t*. The coefficient associated with this variable is expected to be positive. According to Alemayehu and Warner (2004), Individuals between the ages of 40 and 65 spend roughly a quarter of their total lifetime expenses on healthcare. This proportion increases slightly between the ages of 65 and 85. Over a third of a person's total lifetime expenses will be incurred if they live past the age of 85.

Married_{it} is a dummy variable that equals 1 if the respondent is married and 0 otherwise. Wilson and Oswald (2005) argue that marriage benefits people's physical health and can also decrease the likelihood of mental illness. Hence, we expect the coefficient associated with this variable to be negative.

Chronics_{it} represents the number of chronic diseases experienced by individual *i* at time *t*. Similarly, Su et al. (2006) indicate that the main determinant of Catastrophic

Healthcare Expenditure is whether or not a person has a chronic disease. The coefficient associated with this variable is therefore expected to be positive.

$Lincome_{it}$ indicates the logarithm of the average household income of individual i at time t . Molla et al.(2017) find a statistically significant positive relationship between household income and health expenditure through an analysis of data from the Bangladesh Household Income and Expenditure Survey in 2010. Specifically, they observe that a one-tenth rise in household income is associated with one-fiftieth increase in household health expenditure. This could be attributed to the fact that people with higher incomes can afford more expensive healthcare services such as advanced private healthcare, expert consultations, and cutting-edge medical technology. The coefficient associated with this variable is therefore expected to be positive.

$illiterate_{it}$, $primary_{it}$, $secondary_{it}$, $college_{it}$ are all dummy variables indicating education level. $illiterate_{it}$ is a dummy variable equal to 1 if the respondent is illiterate, and 0 otherwise. $primary_{it}/secondary_{it}/college_{it}$ are dummy variables equal to 1 if the person has completed primary/secondary/college education, and 0 otherwise. Huang (2015) investigates the impact of education on individuals' health outcomes and demonstrates that an increase in educational attainment by one year is associated with a reduction of 2 percentage points in the likelihood of experiencing poor health. Therefore, we expect the sign of the coefficient associated with $illiterate_{it}$ to be positive and the sign of the coefficients associated with $primary_{it}/secondary_{it}/college_{it}$ to be negative.

Work_{it} is a dummy variable that represents a respondent's employment status. It takes on a value of 1 if the respondent is presently employed, and 0 if the respondent is currently unemployed or retired. Waddell and Burton (2006) argue that employment generally has a positive impact on both physical and mental well-being, with due consideration given to the characteristics of the job. In contrast, unemployment is linked to diminished physical and mental well-being. Hence, the coefficient associated with this variable is expected to be negative.

Rural_{it} is a dummy variable, taking a value of 1 to represent respondents living in rural areas, and 0 otherwise. According to Fu (2022), rural households exhibit a higher vulnerability to experiencing Catastrophic Health Expenditure (CHE) than those living in urban areas. Hence, it is likely that the coefficient associated with this variable will have a positive sign.

IADLs/ADLs_{it} are limitations in instrumental and basic activities of daily living (IADL/ADLs). Gao et al. (2023) identify a correlation between ADLs, IADLs, and increased expenditures on healthcare. Furthermore, medical costs for disabled older adults are twice as high as for those without disabilities. As a result, we anticipate that the coefficients associated with both variables will be positive.

UEBMI_{it} / URBMI_{it} / NRCMI_{it}/URRMI_{it}/ Private_Health_Insurance_{it} are dummy variables that represent different types of health insurance, with a value of 1 indicating that the individual is covered by the Urban Employee Basic Medical Insurance (UEBMI) / Urban Resident Basic Medical Insurance (URBMI) / New Rural Cooperative Medical Insurance (NRCMI) /Urban and Rural Resident Medical Insurance(URRMI) / Private

Health Insurance (PHI) at time t , and 0 otherwise. According to Li et al. (2020), individuals with health insurance have a 3.4 percentage point higher CHE rate than those without health insurance. From 2000 to 2020, the prevalence of CHE is approximately 13.0 percent for individuals enrolled in the NRCMI program, approximately 12.0 percents for those enrolled in the URBMI program, and approximately 11.9 percent for those enrolled in the UEBMI program. Hence, the coefficient associated with these variables is expected to be positive.

$Smoke_{it}$ is a dummy variable equal to 1 if the respondent smokes, and 0 otherwise. Max (2001) argues that people who smoke have higher overall healthcare costs than people who do not smoke because smoking is associated with a greater number of health problems. We therefore expect the coefficient associated with this variable to be positive.

$Drink_{it}$ is a dummy variable equal to 1 if the individual drank any alcohol in this wave, and 0 otherwise. According to Ronksley et al. (2011), light to moderate alcohol consumption is associated with a lower risk of various cardiovascular diseases. According to Rehm et al. (2017), there is a correlation between the quantity of alcohol consumed and the probability of disease development. Specifically, excessive alcohol consumption raises the risk of diseases like liver and gastrointestinal disorders. Yet, individuals who avoid excessive and sporadic alcohol consumption may still experience positive health effects when engaging in light to moderate drinking. Overall, the sign of the coefficient associated with this variable is not clear.

The error term is made up of the following components:

u_i : This represents an individual fixed effect. This is an unobservable factor that does not change over time and is specific to individual i , and can influence OOP medical expenditure. Individual fixed effects capture individual-specific characteristics that remain constant throughout the study period. We control for this component of the error term by using panel data estimators, which are described in section 4.2.

v_t : This represents a time-fixed effect, which we control by adding time dummies in all our models.

ε_{it} : This is an idiosyncratic error term.

For Hypotheses 1a/1b to hold, β_1 and β_2 need to be statistically significant. Specifically, for U shape relationship, β_1 should be negative and β_2 should be positive.

4.4.1.1.2 Segmented Sleep Duration

Additionally, we study the impact of segmented sleep duration on out-of-pocket (OOP) or catastrophic health expenditure (CHE). We investigate the effects of sleep duration in distinct scenarios: specifically, durations of less than 6 hours, more than 8 hours, and the combined category of less than 6 or more than 8 hours. According to the National Sleep Foundation , the ideal sleep duration for older adults is 7-8 hours (Hirshkowitz et al.,2015). However, our data shows a median of 6 hours. We chose 6-8 hours as the appropriate sleep range. This range covers most of our data and aligns with literature recommendations. It helps us accurately analyse the impact of sleep duration on medical expenses

$$L_OOP_Medical_Expenditure_{it}/Catastrophic_Health_Expenditure_{it} = \beta_0 + \beta_1 * Sleep_Duration_Dummy + \beta_2 * X_{it} + u_i + v_t + \varepsilon_{it} \quad (4-2)$$

Sleep_Duration_Dummy is a categorical dummy variable defined in three distinct ways. In the first definition, it is coded as 1 for individuals with less than 6 hours of sleep duration and 0 for all others. The second definition takes a value of 1 for those who sleep more than 8 hours, with all others coded as 0. The third definition assigns 1 to individuals whose sleep duration is either less than 6 hours or more than 8 hours, and 0 otherwise.

X_{it} contains exactly the same control variables as Equation (4-1). The error term is also identical to the one in Equation (4-1).

For Hypotheses 1a/1b to hold, β_1 associated with Sleep Duration Dummy (<6h / >8h / <6h or >8h) should be positive.

4.4.1.2 Sleep Quality

To test Hypotheses 2, we estimate the following Equation:

$$L_OOP_Medical_Expenditure_{it}/Catastrophic_Health_Expenditure_{it} = \alpha_1 * Good_Sleep_Quality_{it} + \alpha_2 X_{it} + u_i + v_t + \varepsilon_{it} \quad (4-3)$$

Good_Sleep_Quality_{it} is a dummy variable with a value of 1 if the respondent has a good sleep quality, and 0 otherwise.

X_{it} : contains exactly the same control variables as Equation (4-1), namely *gender_i* , *age_{it}* , *chronics_{it}* , *smoke_{it}* , *drink_{it}* , *IADL_{it}* , *ADL_{it}* , *married_{it}* , *Income_{it}* , *work_{it}* , *UEBMI_{it}* , *URBMI_{it}* , *NRCMI_{it}* , *URRMI_{it}* , *Private_Health_Insurance_{it}* , *primary_{it}* , *secondary_{it}* , *college_{it}* , *rural_{it}*

The structure of the error term remains consistent with the structure of Equation (4-1).

α_1 is significant and negative if Hypothesis 2a/2b is valid.

4.4.2 Methodology

We use a two-way fixed effect polynomial model to estimate the relationship between continuous sleep duration and OOP medical expenditure/CHE (i.e., Equation (4-1)). We use a polynomial model because it captures the quadratic relationship. Additionally, this model is intuitive, making it simple to understand and interpret our results (Draper, N. R., & Smith, H, 1998). We use wave (time) and individual fixed effects because of the significant advantage in controlling for unobservable heterogeneity. Individual fixed effects help eliminate bias due to individual invariant traits, while time-fixed effects control for the effects of time trends or policy changes that are common to all individuals. As described by Wooldridge (2010), this dual approach effectively addresses some problems typically associated with panel analyses, such as omitted variable bias and measurement error.

In addition, we use a two-way fixed effect Linear Probability Model (LPM) to estimate Equations (4-2) and (4-3), primarily due to the model's clear interpretability with binary outcomes. Based on previous literature and our hypotheses, we assume these relationships are linear, making the LPM an appropriate choice. Moreover, by incorporating both wave (time) and individual fixed effects, we effectively control for unobservable heterogeneity, which might otherwise bias our results.

To further support our findings, we also use a correlated random effects (CRE) Probit model to estimate Equation (4-2) and Equation (4-3). The CRE probit model is used to test the robustness of the results obtained using the fixed effect linear probability model. This model is especially well-suited to dealing with binary dependent variables like Catastrophic Health Expenditure. According to Wooldridge (2019), CRE methods can be used as a complement to fixed effects methods, with CRE being more applicable to short panels. They can supplement the time heterogeneity and time dependence of fixed effects.

4.5 Data and Descriptive Statistics

4.5.1 Data

Our study makes use of the 2011 to 2018 waves of the China Health and Retirement Longitudinal Study (CHARLS). This dataset includes modules on demographic details, family information, health and insurance, employment, income and consumption, and assets. We merge module data for each wave and then append these into a panel dataset with 75,598 observations. In our study, we focus on middle-aged and older populations. Therefore, we exclude participants younger than 45 years from the CHARLS dataset. This results in the elimination of 250 observations of individuals under 45. For the economic variables in our study, we adjust all monetary data using the Consumer Price Index (CPI) obtained from the National Bureau of Statistics of China. This ensures that our financial data remains consistent and comparable across different years. Additionally, to manage the influence of extreme data points, we apply winsorization to the top and bottom 1 percentage point of all continuous variables. This technique is employed to control the impact of outliers in our analysis. Finally, we refine the dataset further by excluding

observations with missing values for our key regression variables. After that, the final number of observations used in our baseline two-way fixed effect regression analysis is 57,023. Our data processing steps are illustrated in Figure 4.1.

Table 4.1 contains definitions of all variables used in our regressions. Out-of-pocket (OOP) medical expenditures are the sum of out-of-pocket inpatient and out-of-pocket outpatient expenditures. Catastrophic Health Expenditure (CHE) is a dummy variable equal to 1 if a respondent's out-of-pocket medical expenses exceed 40 percentage points of his/her household's capacity to pay (CTP), and 0 otherwise (Xu et al. ,2003). Furthermore, CTP is calculated by subtracting food expenditure from total expenditure. Total annual household expenditures are calculated based on survey responses, where participants report their total spending and food-related expenses. The CHARLS survey further collects detailed data on other categories, such as utilities, transportation, education, and entertainment, providing a comprehensive view of household consumption. By subtracting food expenditures from total spending, we can determine the disposable income available for non-food necessities. This method, widely used in studies like Wagstaff and van Doorslaer (2003) and Xu et al. (2003), helps evaluate catastrophic health expenditures (CHE) and their impact on household financial stability. Analyzing CHE also enables us to explore how sleep patterns influence healthcare costs and the extent of their impact on household finances.

4.5.2 Descriptive Statistics

Table 4.2 presents the descriptive statistics for all variables, including the sample size, mean, standard error, and the range of values, which includes both the minimum and

maximum. The average out-of-pocket medical expenditure within the group is 1,633 Chinese Yuan, with extremes ranging up to 47,025 Yuan. The mean sleep duration, which is our primary independent variable, is measured at 6.268 hours, whereas the average for good sleep quality is observed at 65%. The data shows an average age of nearly 61, a wide range of educational attainment, and a mostly married population. About 47.7% of our sample are male, and 61.1% live in rural areas.

4.6. Results

4.6.1 Baseline Model Results

4.6.1.1 Sleep Duration

4.6.1.1.1 Continuous Sleep Duration

The results of the baseline model of sleep duration are presented in Table 4.3. Column 1 of Table 4.3 reports the estimates of Equation (4-1), aiming to explore the effect of sleep duration on OOP medical expenditure. We observe a U-shaped relationship between night sleep duration and Out-Of-Pocket (OOP) medical expenditure. The coefficient of night-time sleep duration is statistically significant and equal to -0.182, indicating that longer night sleep duration is associated with a lower OOP medical expenditure. In addition, the coefficient for the squared term of night sleep duration is 0.012, which is also significant at the 1 percent level. Taken together, these results jointly convey that the relationship between OOP medical expenditure and night sleep duration initially decreases but starts to increase after a certain point, forming a U-shaped pattern.

Lind and Mehlum (2010) suggest an enhanced test for U-shaped relationships called the U test, which requires that the coefficients of the U-shaped relationship exhibit a

significant decrease on the left side of the extremes and a significant rise on the right side. In Column 1 of Table 4.3, our U test results support that a U-shaped relationship is indeed present. In addition, the U test results also show OOP medical expenditure is minimized at 7.855 hours of night sleep, which is our turning point. To clarify, on the left side of this optimal point, representing shorter sleep durations, we observe a significant decrease in OOP expenditures as sleep duration increases. The slope here is -0.159, indicating that each additional hour of sleep substantially lowers medical expenses up to this optimal sleep duration. Beyond the 7.855-hour threshold, the trend reverses. The slope moderates to 0.073, suggesting a gradual increase in OOP expenditures with longer sleep durations. However, the increase in expenses is less steep compared to the decrease observed for shorter sleep durations. This indicates that while both insufficient and excessive sleep are associated with higher medical costs, the negative health consequences (and thus the increase in medical expenses) are more pronounced with insufficient sleep. This asymmetric U-shaped relationship, characterized by a higher slope on the left and a lower one on the right, is also clearly depicted in Figure 4.2 in the appendix. Figure 4.2 shows that insufficient sleep is associated with a significant increase in medical expenditures, while excessive sleep, although still linked to higher costs, does not increase expenditures to the same extent. This could be due to several factors, such as the greater risk of chronic diseases and impaired immune function associated with sleep deprivation, as supported by existing research (Steptoe et al. ,2006).

These results are consistent with Hypothesis 1a, the optimal duration of sleep is associated with the lowest out-of-pocket health care costs, while shorter and longer sleep durations are associated with higher out-of-pocket medical expenditure. They are

also consistent with Jasani et al. (2020) who argue that maintaining an optimal sleep duration, specifically between 7 and 9 hours, yields benefits in terms of reducing healthcare expenditures. Our research advances the literature by identifying, for the first time, a specific U-shaped relationship between sleep duration and health expenditure, rather than simply dividing sleep duration into different time periods.

Column 2 of Table 4.3 reports the estimates of Equation (4-1) to explore whether there is a U-shaped relationship between sleep duration and catastrophic health expenditures (CHE). It is observed that the coefficient associated with sleep duration and its square are not significant. In light of these results, we explore whether there is a linear relationship between sleep duration and CHE. Excluding the square term of sleep duration, Columns 3 and 4 report the estimates of the determinants of catastrophic health expenditures, respectively, using a fixed effects linear probability model (column 3) and a CRE Probit model (column 4). According to the fixed-effects linear probability model results reported in column 3, the coefficient associated with nighttime sleep duration is significant and equal to -0.003. This implies that each additional unit of nighttime sleep is associated with a 0.3 percentage point lower probability of incurring catastrophic medical expenditures. In addition, according to the results of the CRE Probit model in column 4, the coefficient on nighttime sleep duration is also significant and equal to -0.003, which further supports the previous outcome.

These findings are not in line with Hypothesis 1b, which suggests that the relationship between sleep duration and Catastrophic Health Expenditure could be U-shaped. Based on our results, the connection between sleep duration and Catastrophic Healthcare

Expenditure (CHE) appears to be predominantly linear. This can be explained by considering that CHE often involves substantial and unpredictable medical costs that are frequently associated with severe health issues. According to our previous analyses, the negative slope is steeper when sleep duration is shorter than the optimal duration, implying that sleep deprivation significantly increases medical expenditures. Meanwhile, while excessive sleep is also associated with higher medical expenditures, this increase is relatively small and may not have reached the level of CHE.

Focusing on the control variables, Table 4.3 further shows a positive association between the number of chronic diseases and Out-of-Pocket (OOP) expenditures and Catastrophic Health Expenditure (CHE). This is in line with our expectations and consistent with other literature. Wang et al. (2019) also identify that chronic disease and healthcare expenditures are positively correlated for elderly Chinese people. From Table 4.3, It is evident that there is a positive relationship between income and OOP, whereas there is a negative relationship between income and CHE. The former finding is consistent with Molla et al. (2017), who observe that a ten percentage point rise in household income is associated with a two percentage point increase in household healthcare expenditure. This is because people with higher incomes may choose more expensive healthcare. The latter finding is consistent with Parker and Wong (1997), who also find a negative relationship between income and CHE, indicating that higher income is associated with a lower probability of incurring CHE. UEBMI and NRCMI are both positively associated with OOP, with the coefficient associated with NRCMI being greater than that associated with UEBMI. This can be explained by considering that NRCMI has lower reimbursement rates and more reimbursement restrictions, such as provider type and prescription

coverage, than the UEBMI (Meng and Tang, 2010). As a result, those with an NRCMI must pay greater out-of-pocket medical expenditures for some medical treatments or prescriptions.

Table 4.3 also demonstrates that being married is associated with lower OOP medical expenditure and a lower probability of incurring CHE. This result aligns with our expectations and is consistent with previous research, which suggests that marriage has a positive impact on individuals' physical and mental health (e.g., Wilson and Oswald, 2005). In addition, we observe that work is also negatively associated with OOP medical expenditure and CHE. This finding is consistent with Waddell and Burton (2006) who argue that employment is associated with better health outcomes, while unemployment is associated with a deterioration in health. Furthermore, drinking alcohol is associated with lower OOP medical expenditure and a lower risk of incurring CHE. This association might be partially explained by research suggesting beneficial health effects of moderate or low alcohol consumption (e.g., Ronksley, 2011; Rehm, 2017). However, it is important to note that the alcohol consumption variable in our study, represented as a dummy variable indicating whether alcohol is consumed within the year, does not consider the frequency or quantity of intake.

4.6.1.1.2 Segmented Sleep Duration

This section explores segmented sleep duration, focusing on three distinct scenarios. The first scenario involves individuals who sleep for less than six hours, the second involves

those who sleep for less than six hours or exceed eight hours, and the third scenario specifically focuses on individuals who sleep for more than eight hours.

Table 4.4 illustrates the scenario of sleeping less than six hours, based on Equation (4-2). From column (1), we can observe that the coefficient associated with the sleep duration dummy is statistically significant and equal to 0.176. This indicates that sleeping less than six hours is associated with a 19.24 percentage points higher value of out-of-pocket (OOP) medical expenses²⁹. Similarly, column (2) shows that sleeping less than six hours is associated with a 1.2 percentage point higher likelihood of incurring catastrophic health expenditures (CHE).

Table A4.14 (in Appendix) presents results on the scenario of sleeping less than six hours or more than eight hours, drawing from Equation (4-2). From column (1), we can observe that a sleep duration of less than six hours or more than eight hours is associated with a 13.09 percentage point higher out-of-pocket (OOP) expenses³⁰. In contrast, column (2) does not show a significant relationship between sleep duration of less than six hours or more than eight hours and catastrophic health expenditures (CHE). This shows that sleeping less than 6 hours or more than 8 hours increases medical expenses but does not cause CHE. The coefficients associated with the control variables are generally similar to those shown in Table 4.3.

Table A4.15 (in the Appendix) presents the estimates of Equation (4-2) as a function of a dummy equal to 1 if the individual sleeps for more than eight hours, and 0 otherwise.

²⁹ This number is obtained as follows: $e^{0.176}-1$, resulting in 19.24%.

³⁰ This number is obtained as follows: $e^{0.123}-1$, resulting in 13.09%.

No significant association is found between these variable and OOP (column 1) and CHE (column 2).

In summary, a sleep duration of less than six hours is associated with increased OOP expenses and a higher likelihood of CHE. In contrast, sleeping less than six hours or more than eight hours is linked with a significant decrease in out-of-pocket (OOP) medical expenses, but it does not significantly affect catastrophic health expenditures (CHE). On the other hand, sleeping more than eight hours does not show a significant impact on either OOP expenses or CHE. This is consistent with our hypothesis 1a, too short or too long sleep duration is associated with higher healthcare expenditure.

4.6.1.2 Sleep Quality

The results of the baseline model aimed at estimating the effects of sleep quality on medical expenditures are displayed in Table 4.5. Column 1 represents the regression results for Equation (4-3), aiming to explore the impact of sleep quality on OOP medical expenditure. Based on the results shown in Column 1, it can be observed that the coefficient estimate for good sleep quality is statistically significant and equal to -0.249. This indicates that good sleep quality is associated with a 22.04 percentage points lower OOP medical expenditure.³¹ This association can likely be attributed to the positive

³¹ This number is obtained as follows: $e^{-0.249} - 1$, resulting in 22.04%.

impact of good sleep quality on health, particularly in terms of enhancing people's immune function and reducing vulnerability to diseases.³²

Column 3 of Table 4.5 displays the estimates of Equation (4-3), which looks at the association between CHE and good sleep quality. A linear probability model with fixed effects is used in estimation. We observe that good sleep quality is associated with a 1.4 percentage point lower probability of accruing Catastrophic Health Expenditure (CHE). Similar results are obtained in column 4, where a CRE Probit estimator is used. The effects of the control variables are similar to those in the previous Tables.

4.6.2 Robustness Checks

4.6.2.1 Generalized Method of Moments (GMM)

To address potential endogeneity, including reverse causality, we estimate our model using the System Generalized Method of Moments (System GMM) approach (Blundell and Bond, 1998). Sleep duration and quality may be endogenous, as sleep patterns can influence medical expenses, while high medical costs can cause stress, making it difficult for people to sleep. The System Generalized Method of Moments (System GMM) is particularly suitable for our unbalanced panel data, which is characterized by a large number of cross-sectional units (N) and a short time dimension (T). System GMM could generate a large number of instrumental variables by using both level and differenced equations.

³² Irwin (2019) reveals that sleep has a positive impact on immunological barrier defences and also observes that individuals with sleep disorders, which result in inflammation, exhibit increased vulnerability to diseases.

This method improves the effectiveness of the instrumental variables, which can enhance the reliability of our analysis.

We postulate that our main independent variables, namely sleep duration and its square term ($Night_Sleep_Duration_{it}$, $Night_Sleep_Duration_sq_{it}$) and sleep quality ($Good_Sleep_Quality_{it}$) are endogenous. This implies that these variables are potentially influenced by unobserved factors within our model. Additionally, we assume endogeneity in our control variables, which include

$chronics_{it}$, $smoke_{it}$, $drink_{it}$, $IADL_{it}$, ADL_{it} , $married_{it}$,
 $Income_{it}$, $work_{it}$, $UEBMI_{it}$, $URBMI_{it}$, $NRCMI_{it}$, $URRMI_{it}$,
 $Private_Health_Insurance_{it}$, $primary_{it}$, $secondary_{it}$, $college_{it}$, $rural_{it}$.

This assumption recognizes that these control variables may also be affected by unobserved variables, leading to potential biases in our estimations if not appropriately addressed. The endogeneity of these variables mainly comes from two-way causality and omitted variable bias. To address endogeneity, our method involves using the same variables lagged by at least two periods as instruments. These potential endogenous variables lagged by at least two periods are not affected by the current situation, and can thus be considered as valid instruments (Bond, 2002).

Furthermore, we also include the average daily sunshine hours ($D_SunshineHour$) as an additional exogenous instrument. $D_SunshineHour$ is the average daily sunshine duration at the municipal level, covering the period from 2011 to 2018. The average daily duration of sunshine is considered as an exogenous variable, as the number of sunshine hours is mostly determined by natural meteorological patterns.

A number of papers have highlighted an association between the duration and quality of sleep and sunshine hours. For instance, according to Düzgün and Akyol (2017), two hours of direct sunshine in the morning on consecutive days enhances the overall scores of sleep quality. Similarly, Muscogiuri et al.(2019) demonstrate that sunshine exposure has a significant role in the synthesis of vitamin D, which in turn is closely associated with the regulation of a regular sleep-wake cycle.

We also estimate our model using the Forward Orthogonal Deviations (FOD) transformation, as proposed by Arellano and Bover (1995). The utilization of this approach ensures a defined value for the majority of observations, reducing the influence of missing data.

In addition, to ensure the validity of the instruments and the adequacy of our specifications, we perform a Hansen test for overidentifying restrictions. Furthermore, the Arellano-Bond test is used to check the autocorrelation of the differenced residuals. It is anticipated that there is no second-order autocorrelation (AR(2)), which confirms the instruments are valid.

4.6.2.1.1 GMM Model Results (Sleep Duration)

Table 4.6 presents the findings of the Generalised Method of Moments (GMM) estimates of Equation (4-1). From column (1), we can observe a U-shaped relationship between Out-of-Pocket (OOP) medical expenditure and night sleep duration. This is consistent with our hypothesis 1a. and with the baseline results. In the analysis presented in

column (2), the data fails to support a U-shaped relationship between sleep duration and Catastrophic Health Expenditure (CHE). Based on these findings, we exclude the squared term of sleep duration from Equation (4-1) to refine our model, as shown in column (3). The analysis of column (3) reveals that the coefficient associated with sleep duration is still negative and significant, aligning with the findings of our baseline model.

Regarding the control variables of the robustness model, it is observed that the coefficients associated with key factors such as chronic conditions, income, and ADLs are largely consistent with the results of the baseline model. While in the baseline model, the influence of gender is omitted due to the presence of individual-fixed effects. In the GMM model, male displays a positive correlation with out-of-pocket (OOP) medical expenditures. Furthermore, while smoking dose not present significant effects in the baseline model, it is positively associated with catastrophic health expenditure (CHE) in the GMM model. This may because, in the GMM model, the endogeneity like reverse causality of these variables is better addressed, revealing their true effects on medical expenditure. This is consistent with Max (2001) who argue that people who smoke on a regular basis are more likely to have higher medical expenditures over the course of their lifetimes.

In addition, the P values for the Hansen test indicate that the selection of instruments is not overidentified. Furthermore, the AR(2) p-values are consistently not significant across all columns, which shows no second-order autocorrelation in the differenced residuals. This suggests that the instruments used are suitable and are not

correlated with the error term. Both the Hansen test and AR(2) test support the model's validity.

4.6.2.1.2 GMM Model Results (Sleep Quality)

The findings of the Generalised Method of Moments (GMM) estimation for good sleep quality derived from Equation (4-3) are presented in Table 4.7. In Column (1), we still observe that good sleep quality is associated with lower OOP medical expenditure. As shown in column (2), we can observe that good sleep quality is associated with a 17 percentage point lower probability of accruing CHE. The negative relationships between good sleep quality and OOP/CHE are also consistent with our hypotheses and the results of the baseline model.

In terms of the control variable, we can see that chronic diseases and health insurance are associated with higher OOP medical expenditure, consistent with our baseline model. However, while the baseline model shows no significant impact of college education on OOP medical expenditure, the Generalized Method of Moments (GMM) model indicates that having a college degree or higher is associated with lower medical expenditure. In addition, while the baseline model shows that there is no relationship between primary education and CHE, the GMM model shows a negative association between having primary education and the probability of incurring CHE. This is consistent with Huang (2015) who argue that education attainment is negative associated with healthcare expenditure.

Finally, both the Hansen and the AR(2) test confirm the validity of our instruments.

4.6.2.2 Estimation on a Matched Sample

We next investigate the influence of segmented sleep duration and sleep quality on medical expenditures on a matched sample. When dividing the sample by segmented sleep duration or sleep quality may cause comparability problems. To this end, we apply the propensity score matching (PSM) method developed by Rosenbaum and Rubin (1983). This method helps to make the groups more similar and ensures better comparability. The treatment group with appropriate sleep duration is matched with those who have inappropriate sleep duration but are similar in other personal characteristics. Similarly, the treatment group with good sleep quality is matched with those with poor sleep quality but similar in other personal traits. We compare these groups in terms of healthcare expenditures while effectively controlling for underlying personal characteristic differences.

When estimating the propensity score which help match individuals from different groups, a logit model is employed. We incorporate social economics and lifestyle characteristics as the main predictors for assessing sleep-related variables(sleep duration/sleep quality), alongside additional personal characteristics such as age and gender. This mitigates the potential influence of selection bias from differences in individuals' conditions. As suggest by Imbens and Rubin (2015), we use lagged terms for the social economics variables and lifestyle variables to reduce potential post-treatment

bias. This because current measurements may not have an immediate effect on health expenditures. However, lagged terms allows for a more accurate assessment of long-term effects. This model can be expressed as follows:

$$\begin{aligned} & \text{Sleep_Duration_Dummy}_{it} / \text{Good_Sleep_Quality}_{it} = \\ & \alpha_0 + \alpha_1 \text{socioeconomic}_{it-1} + \alpha_2 \text{lifestyle}_{it-1} + \alpha_3 \text{Age}_{it} + \alpha_4 \text{gender}_{it} + \varepsilon_{it} \end{aligned} \quad (4-4)$$

Sleep_Duration_Dummy_{it} is a dummy variable equal to 1 for the treatment group, i.e. for individuals who maintain (in turn) a sleep duration of less than 6 hours, greater than 8 hours, or between 6 to 8 hours, and 0 otherwise.

socioeconomic_{it-1} including *Married_{it-1}*, *lincome_{it-1}*, *work_{it-1}*, *UEBMI_{it-1}*, *URBMI_{it-1}*, *NRCMI_{it-1}*, *URRMI_{it-1}*, *Private_Health_Insurance_{it-1}*

lifestyle_{it-1} including *smoke_{it-1}*, *drink_{it-1}*, *chronics_{it-1}*

Following Gu and Rosenbaum (1993), the one-to-one nearest-neighbour matching approach is applied due to its directness and accuracy. This approach involves identifying an individual from the control group with the propensity score most similar to each individual in the treatment group. However, the one-to-one nearest-neighbor matching approach has some limitations, such as excluding unmatched units, relying on the Conditional Independence Assumption (CIA), and needing sufficient overlap in propensity score distributions. Despite these limitations, this method remains a practical and effective method for achieving accurate and interpretable estimations.

In order to evaluate the quality of matching, we perform balancing tests as proposed by Rosenbaum and Rubin (1985). These tests assess the balance of key variables like

socioeconomic factors between the treatment and control groups before and after matching. Maintaining balance is important to confirm that any differences in outcomes after the intervention are not due to pre-existing differences between the groups.

4.6.2.2.1 Estimation of the Effects of Segmented Sleep Duration in a Matched Sample

Table 4.8 shows the results of the logit model for estimating the propensity score, as described in Equation (4-4). This table is divided into three columns based on the duration of sleep in the treatment group. The first column displays the results for the groups that slept for less than 6 hours or more than 8 hours. The second column contains specific results for those in the treatment group who slept for less than 6 hours. Finally, the third column focuses on treatment group respondents who sleep for more than 8 hours. The results from Table 4.8 demonstrate significant associations between different personal characters and sleep durations.

The results of the balancing tests for different treatment groups based on their sleep durations are presented in Table A4.16, Table A4.17, and Table A4.18, which can be found in the Appendix. Specifically, Table A4.16 presents results for the group that sleeps less than 6 hours or more than 8 hours, Table A4.17 for the group that sleeps less than 6 hours, and Table A4.18 shows the results for those sleeping more than 8 hours. These tables provide detailed comparisons of the various variables involved in the matching process, respectively. They show the mean values of all variables before and after

matching. In addition, these tables show the level of bias before and after matching, as well as the percentage reduction in bias due to the matching process. From the results, we observe a significant reduction in bias for each variable following the matching process. We can also observe that the mean bias decreased from more than 10% before matching to less than 3% after matching, indicating that the matching process significantly improved the comparability between the treatment and control groups.

Furthermore, to visually evaluate the distribution of propensity scores, kernel density plots are generated both before and after matching, as suggested by Smith and Todd (2005). This approach allows for a more intuitive comparison of the propensity score distributions before and after the matching process. The results are shown in Figure 4.3, Figure A4.5, and Figure A4.6, which can be found in the Appendix. Specifically, Figure 4.3 illustrates the scenarios where the treatment group's sleep duration is less than 6 hours. Figure A4.5 focuses on the treatment group sleeping for less than 6 or more than 8 hours. Lastly, Figure A4.6 depicts the treatment group with more than 8 hours of sleep. The upper sections of these figures (Figure 4.3, Figure A4.5, and Figure A4.6) display the kernel density distributions before matching, while the lower sections illustrate the distributions after the matching. It is evident from these figures that the distribution of propensity scores differs substantially between the treatment and control groups before matching. The difference between the treatment and control groups becomes smaller and more comparable after matching. This implies that the covariate balance is enhanced as a result of the matching process.

Table 4.9 displays the estimates of Equation (4-2), performed on a matched sample. In column (1), the coefficient associated with the `Sleep_duration_Dummy` is statistically significant and equal to 0.138, which means that sleeping less than 6 hours is associated with a 14.8 percentage point higher OOP medical expenditure³³. This implies that insufficient sleep duration(<6h) can potentially lead to higher OOP medical expenditure. As indicated in column (2), the coefficient for `Sleep_duration_Dummy` is statistically significant and equal to 0.011, indicating that individuals who sleep less than 6 hours have a 1.1 percentage point higher likelihood of experiencing Catastrophic Health Expenditure (CHE). This aligns with the estimates from the whole sample analysis.

The effects of some key control variables, such as marriage, chronic diseases, income, work, and drink, as well as IADLs and ADLs, are similar to those highlighted when discussing the baseline model. However, there are still some differences, such as illiteracy and primary become significant in matched sample. In terms of health insurance, in matched sample, the effect of UEMBI on OOP medical expenditure is no longer significant, whereas the effect of URBMI becomes significant.

Table A4.19 focuses on people who sleep less than 6 hours or more than 8 hours, and Table A4.20 only concentrates on people who sleep more than 8 hours. According to Table A4.19, people who sleep less than 6 hours or more than 8 hours also have higher OOP medical expenditure and a higher risk of CHE. According to Table A4.20, people who sleep more than 8 hours have no association with OOP medical expenditure and Catastrophic health expenditure. In addition, the direction and significance of the control

³³ The figure is obtained as follows: $e^{0.138} - 1$, resulting in 14.8%.

variables in Table A4.19 and Table A4.20 are essentially all in line with Table 4.9. The only disparity observed is the emergence of a statistically significant association between sleep durations of less than 6 or more than 8 hours and catastrophic health expenditures (CHE) in the context of the matched sample analysis. The reason for the slight differences between baseline results on the whole sample and regression results on the matched sample is that baseline results may still be affected by pre-existing differences between individuals in the sample.

4.6.2.2.2 Estimation of Sleep Quality in a Matched Sample

Table 4.10 shows the results of the logit model for estimating the propensity score, as described in Equation (4-4). As observed in Table 4.10, similar to the findings in Table 4.8, various personal characteristics are correlated with sleep quality.

The balancing test results are presented in Table A4.21 in the Appendix. This table provides a detailed comparison of the various variables involved in the matching process. It specifically shows the mean values of all variables before and after the matching. Additionally, the table displays the level of bias both before and after matching, and the percentage reduction in bias. The results indicate a significant reduction in bias for each variable after the matching. This decrease in percentage bias shows that the matching process has effectively enhanced the comparability between the treatment and control groups.

Furthermore, the results of the kernel density plots are shown in Figure 4.4. Specifically, the upper section of Figure 4.4 displays the kernel density distributions before matching, while the lower sections illustrate the distributions after the matching. Before matching, we observe that the distribution of propensity scores differs significantly between the treatment and control groups. After matching, the difference between the treatment and control groups becomes smaller and more comparable. As a result of the matching process, the covariate balance is improved.

Table 4.11 shows the results of Equation (4-3), which uses matched data to evaluate the impact of sleep quality on OOP medical expenditure/CHE. In Column (1), we observe that the coefficient associated with `Good_Sleep_Quality` is -0.238, indicating that better sleep quality is associated with a 21.2 percentage point lower out-of-pocket medical expenses. Column (2) shows that the coefficient associated with `Good_Sleep_Quality` is -0.015, indicating that individuals with better sleep quality are associated with a 1.5 percentage point lower probability of accruing Catastrophic Health Expenditure (CHE). These findings are consistent with the predictions of our baseline model and support our hypothesis. As for control variables, the outcomes are essentially identical to those of the previous results and our baseline model. For example, marriage, employment, and alcohol consumption are associated with lower OOP and reduced risk of CHE. By contrast, chronic diseases, health insurance, and ADLs/IADLs are associated with higher OOP, and ADLs /IADLs are also associated with a higher probability of CHE.

This evidence further reinforces the robustness of our baseline model, as it remained consistent even after adopting terms to mitigate potential biases during the process of

matching the control group with the treatment group based on various socioeconomic and chronic disease characteristics.

4.6.3 Mediation Analysis

To obtain a deeper understanding of the relationship between sleep and medical expenses, we incorporate inpatient and outpatient visits as mediating factors in our analysis. This approach allows us to precisely assess the indirect impact of sleep duration/quality on healthcare expenditures. According to Choi et al.(2017), there is a positive correlation between both shorter and longer durations of sleep and a higher rate of healthcare utilization in the US. Additionally, Fan et al. (2022) argue that Inpatient visit frequency is disproportionately linked to healthcare spending, with the top 10% of patients by hospitalization frequency accounting for almost 50% of total medical expenses. In light of these findings, we investigate the relationship between sleep and healthcare expenditure by utilizing the frequency of outpatient/inpatient visits as mediating factors. This is because outpatient visits and inpatient visits can cover a wide range of illnesses ranging from mild to severe. Outpatient visits typically address stable chronic diseases and less severe health issues, whereas hospitalizations pertain to more acute and severe conditions. By analyzing the mediating impact of the frequency of use of outpatient and inpatient services, we can gain a deeper understanding of the pathways through which sleep affects medical expenditure, specifically determining

whether sleep primarily affects costs through outpatient services or hospitalizations. In addition, in the context of China, such comparisons are particularly important due to the substantial disparities in the reimbursement rates for outpatient and inpatient services across different provinces within the public health insurance system. Xu et al. (2023) argue that outpatient services are typically reimbursed at a lower rate compared to inpatient services.

Firstly, we choose a three-step mediation model (Baron and Kenny, 1986), which takes the following form:

$$L_OOP_Meedical_Expenditure_{it}/Catastrophic_Health_Expenditure_{it} = \alpha_1(Sleep_Duration_Dummy/Good_Sleep_Quality) + \alpha_2 X_{it} + v_i + u_t + e_{it} \quad (4-5)$$

$$Inpatient_Frequency_{it}/Outpatient_Frequency_{it} = \beta_1(Sleep_Duration_Dummy/Good_Sleep_Quality) + \beta_2 X_{it} + v_i + u_t + e_{it} \quad (4-6)$$

$$L_OOP_Meedical_Expenditure_{it}/Catastrophic_Health_Expenditure_{it} = \gamma_1(Inpatient_Frequency_{it}/Outpatient_Frequency_{it}) + \gamma_2(Sleep_Duration_Dummy/Good_Sleep_Quality) + \gamma_3 X_{it} + v_i + u_t + e_{it} \quad (4-7)$$

$Inpatient_Frequency_{it}$ represents the annual frequency of inpatient visits for individual i in year t .

$Outpatient_Frequency_{it}$ represents the annual frequency of outpatient visits for individual i in year t .

X_{it} contains the same set of control variables as before. Many of the determinants impacting OOP/CHE, such as socioeconomic status, insurance coverage, health status,

and household income, are also recognized as pivotal in shaping healthcare-seeking behaviors, including both inpatient and outpatient visits.

Next, we use the Sobel test (Sobel, 1982) to verify the significance of these mechanisms. While the three-step mediation model is straightforward and comprehensible, the Sobel Test offers a more precise approach to quantifying the magnitude and significance of the mediation effect. The following process is used for estimation:

Firstly, we estimate the coefficient β_1 from Equation (4-6), representing the impact of the independent variable on the mediator.

Secondly, we calculate γ_1 from Equation(4-7), representing the impact of the mediator on the dependent variable when controlling the independent variable.

Then, we can calculate the indirect effect (mediating effect) as $\beta_1 * \gamma_1$

Finally, we calculate the Sobel statistic =
$$\frac{\beta_1 * \gamma_1}{\sqrt{Var(\beta_1) * \gamma_1^2 + Var(\gamma_1) * \beta_1^2}}$$

When assessing the p-value associated with the Sobel statistic, a significant result indicates that the mediator significantly influences the relationship between the independent and dependent variables.

Through the combined application of the three-step method and the Sobel test, we enhance the robustness of our conclusions regarding the mediating effects between sleep variables and OOP/CHE, ensuring they are not only comprehensive but also statistically robust.

4.6.3.1 Mediation Effect Results (Sleep Duration)

Table 4.12 presents the results of the mediation effects analysis on sleep duration, as estimated from Equations (4-5) to (4-7). Columns (1) and (2) focus on the role of outpatient frequency as a mediator in exploring the impact of sleeping less than 6 hours on out-of-pocket healthcare expenditure/Catastrophic health expenditure (OOP/CHE). In Column (1), we observe that the Step 1 Coefficient (α_1) from Equation (4-5) is statistically significant, indicating that sleeping less than 6 hours is associated with higher OOP. The Step 2 Coefficient (β_1), valued at 0.053 from Equation (4-6), suggests that individuals with less than 6 hours of sleep duration tend to have more frequent outpatient visits. In Step 3, outlined by Equation (4-7), the model incorporates the mediator as a control variable, differing from Step 1. Both Coefficients γ_1 and γ_2 are found to be significant. When the mediator is considered, the direct effect of insufficient sleep duration(<6h) on OOP/CHE, represented by γ_2 (0.112), is less than the total effect α_1 (0.170), suggesting the presence of a partial mediating effect. This finding is further supported by a statistically significant Sobel test statistic of 3.147, confirming the mediator's significant role.

The results for CHE in Column (2) are quite similar to those for OOP in Column (1). The only difference is the Step 3 Coefficient (γ_2). When the mediator outpatient frequency is considered, the direct effect of sleep duration(<6h) on CHE is not significant, suggesting the presence of a fully mediating effect. Furthermore, the significance of this mediation effect is also supported by a statistically significant Sobel test statistic of 2.977.

Our analysis in Columns 3 and 4 investigates the role of inpatient frequency as a mediator in the relationship between insufficient sleep (less than six hours) and OOP medical expenditure/ Catastrophic Health Expenditure. The results demonstrate that the Step 2 Coefficient (β_1) in Equation (4-6) is not statistically significant in either column, indicating that there is no significant relationship between the mediator (inpatient frequency) and the independent variable (less than 6 hours sleep duration). Furthermore, the Sobel test statistics are not significant in both columns, reinforcing the finding that inpatient frequency does not act as a mediator in this context. These outcomes suggest that the impact of insufficient sleep(less than 6 hours) on OOP/CHE is more likely through conditions typically managed in outpatient settings rather than through those requiring inpatient care. This could be because conditions related to insufficient sleep duration (less than 6 hours) are generally not severe or urgent, such as certain stable chronic conditions (like diabetes and hypertension), mild infectious diseases (such as the common cold), and sleep-related disorders (including insomnia and sleep apnea).

In the previous section, we also discovered a significant correlation between the sleep duration variable (sleep duration less than 6 hours or greater than 8 hours) and medical expenditure. To better understand this relationship, we assess the potential mediating roles played by the frequency of inpatient and outpatient visits. The results are displayed in Table A4.22, which can be found in the Appendix. From this table, we can still observe that the frequency of outpatient visits has a significant mediating impact on OOP medical expenditure, whereas inpatient visits do not. This is consistent with the mediating results of insufficient sleep duration(<6h).

4.6.3.2 Mediation Effect Results (Sleep Quality)

Table 4.13 displays the estimates of Equations (4-5) to (4-7), focusing on the effects of sleep quality. Columns (1) and (2) concentrate on examining the role of outpatient frequency as a mediator in evaluating the impact of good sleep quality on Out-of-Pocket (OOP) and Catastrophic Health Expenditures (CHE), respectively. In Column (1), the Step 1 Coefficient (α_1), as derived from Equation (4-5), demonstrates statistical significance, indicating that good sleep quality is associated with a decrease in OOP. Furthermore, the Step 2 Coefficient (β_1) from Equation (4-6) implies that individuals with good sleep quality typically experience a 7.1 percentage point reduction in the frequency of outpatient visits. Step 3 modifies Step 1 by incorporating the mediator as an extra control variable (see Equation (4-7)). Both coefficients γ_1 and γ_2 are statistically significant. When the mediator is considered, the absolute value of γ_2 (-0.151), is less than the total effect α_1 (-0.228), suggesting the presence of a partial mediating effect. This finding is further supported by a statistically significant Sobel test statistic, confirming the mediator's significant role. Column (2) presents results that are remarkably similar to those in Column (1). We can also observe that the impact of good sleep quality on Catastrophic Health Expenditure is partially mediated by inpatient frequency. Furthermore, the significance of this mediation effect is also supported by the Sobel test statistic.

Columns 3 and 4 focus on the role of inpatient frequency as a mediator. The Step 1 Coefficient (α_1), Step 2 Coefficient (β_1), Step 3 Coefficient (γ_1), and

Step 3 Coefficient (γ_2) are all significant, and the absolute value of γ_1 is smaller than α_1 , indicating a partial mediating effect.

Furthermore, the impact of outpatient visits on the association between good sleep quality and Out-of-Pocket or Catastrophic Health Expenditure (OOP/CHE) is considerably stronger when compare to inpatient visits. Specifically, the indirect impact of the frequency of outpatient visits on the relationship between sleep quality and out-of-pocket expenses, as indicated in column (1), is -0.0769 ($P < 0.01$). In contrast, the indirect effect of inpatient visit frequency, detailed in column (3), is only e -0.0389 ($P < 0.05$).

Similarly, when examining the impact of good sleep quality on CHE, the comparison of indirect effects in columns (2) and (4) reveals that the mediating influence of outpatient frequency is twice as large as that of inpatient visits. This suggests that sleep quality more likely influences conditions typically managed in outpatient settings rather than those requiring inpatient care. These findings also imply that there should be a consideration for increasing the reimbursement rates for outpatient services.

4.7 Conclusion

This paper focuses on the impact of sleep on medical expenditure. By examining the effects of sleep duration and sleep quality on OOP medical expenditures and Catastrophic Healthcare Expenditures (CHE), we have come to the following conclusions:

Firstly, for middle-aged and elderly people, the relationship between OOP medical expenditure and night sleep duration initially decreases but starts to increase after a certain point, forming a U-shaped pattern. Both our baseline model and the Generalized Method of Moments (GMM) model consistently reveal the presence of this U-shaped relationship. The slope is notably steeper on the left and slower on the right. This pattern indicates that sleep deprivation plays a more significant role in the increase of medical expenses than excessive sleep. Therefore, we strongly recommend avoiding sleep deprivation and consistently adhering to a moderate sleep schedule to mitigate out-of-pocket (OOP) healthcare expenditures. We also find that a higher sleep duration is negatively associated with CHE.

Secondly, better sleep quality is associated with lower OOP medical expenditure and a reduced risk of CHE in middle-aged and older adults. This further stresses the importance of integrating sleep quality into public health policies and personal health management, particularly for middle-aged and older populations. These results are robust to using GMM and to estimating our models on matched samples.

Thirdly, we perform mediation tests utilizing both the three-step and Sobel tests. The findings consistently indicate that the frequency of outpatient visits serves as a mediating factor between sleep duration/sleep quality and OOP medical expenditure/CHE. Inpatient frequency also serves as a mediator for sleep quality and OOP/CHE. The analysis also reveals that outpatient frequency has a stronger mediation impact than inpatient frequency on sleep quality. Outpatient departments typically handle stable chronic and other mild conditions, while inpatient departments are

responsible for acute and severe disorders. The findings indicate that outpatient visits have a more significant role in mediating the relationship between sleep duration and quality, and healthcare expenditures. This suggests that sleep duration and quality have a greater impact on medical costs by influencing the occurrence and treatment of minor infectious diseases and stable chronic diseases. This implies the potential efficacy of enhancing sleep to prevent and control common diseases, consequently offering significant prospects for alleviating the overall strain on the healthcare system.

Based on our findings, we make the following policy recommendations. Firstly, the public health sector should take measures to improve the quality of sleep of the general public. These include educational campaigns to raise public awareness of good sleep hygiene, incorporating sleep quality assessment into routine health check-ups, and implementing night-time noise control policies to create a better sleeping environment.

Furthermore, considering the significant impact of sleep duration on medical expenditure, it is necessary for policies regarding working and school hours to prioritize providing individuals with an adequate amount of sleep. Furthermore, it is important to establish appropriate regulations for the opening hours of nighttime entertainment businesses, such as shopping malls, in order to minimize any adverse effects on the public's sleep schedule.

Finally, given that the frequency of outpatient visits demonstrates a more significant mediating effect compared to inpatient visits, it is crucial for public health insurance policymakers to re-evaluate the reimbursement rates for outpatient services. In China, public health insurance reimbursement rates for outpatient care are generally lower than those for inpatient care. Therefore, it is advisable to increase the reimbursement ratio for outpatient services. This is particularly crucial given the observed significant higher mediating effect of the frequency of outpatient visits on Sleep and Catastrophic Health Expenditure (CHE).

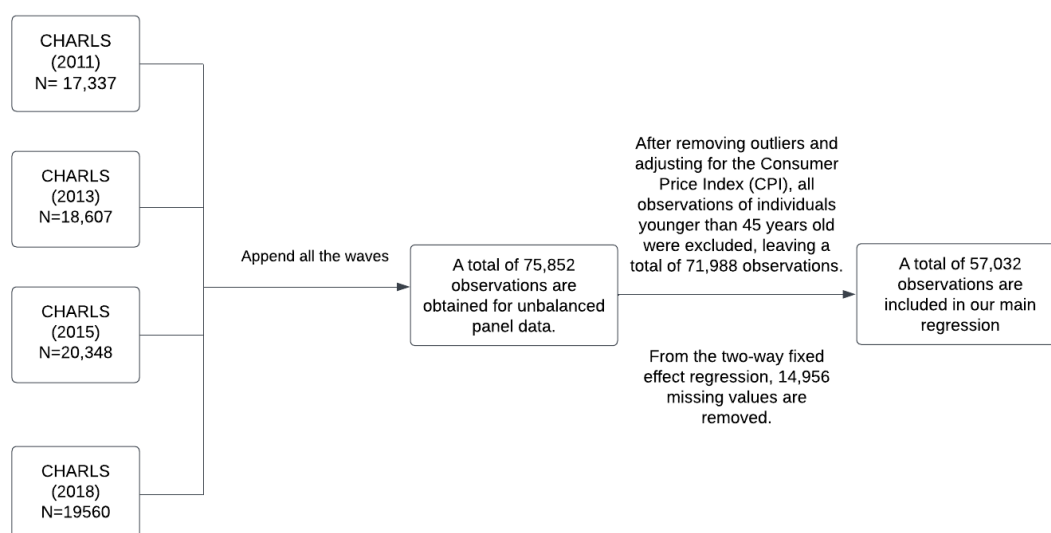
Our paper suffers from some limitations. Firstly, the self-reported measures for sleep duration and quality may lead to some degree of reporting bias. Although we have employed instrumental variables in an attempt to mitigate these biases, they cannot be entirely eliminated. Furthermore, the applicability of our study is rather limited, as our dataset exclusively includes persons who are 45 years old and older, with a specific emphasis on the middle-aged and elderly population. Thus, our research findings may not be directly applicable to younger age groups.

Future research could focus on exploring the unique sleep problems faced by different age and occupational groups (e.g., children, older adults, and night shift workers), as well as customized sleep intervention programs designed for these specific groups. Furthermore, it will be crucial to conduct a thorough examination of the cost-effectiveness of different sleep interventions, such as cognitive behavioral therapy for

insomnia (CBT-I)³⁴ and pharmacological treatments. These studies will enable us to better understand how to effectively improve sleep while optimizing the efficient use of healthcare resources.

Figures and Tables for Chapter 4

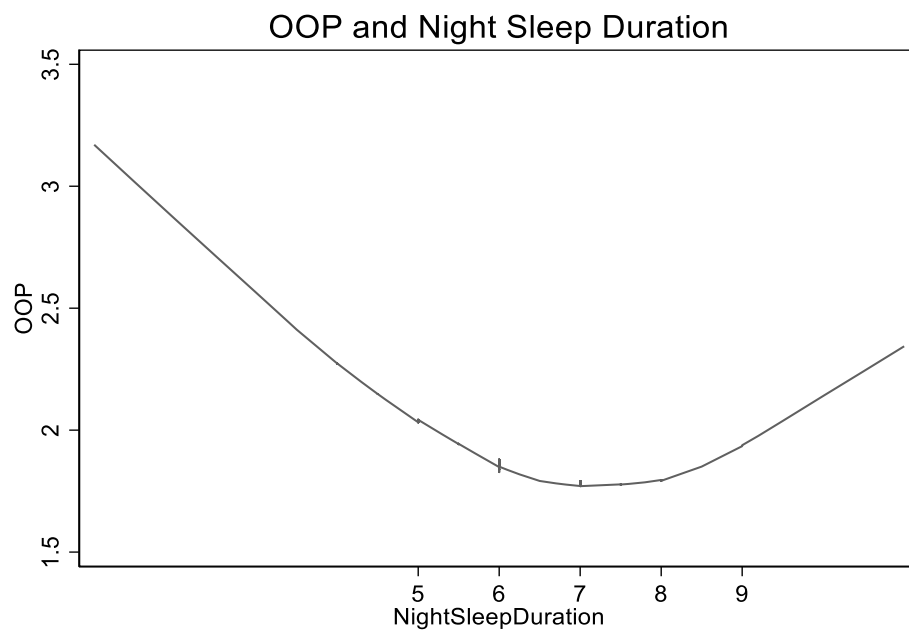
Figure 4.1 Data Processing



Note: This flow chart outlines the data processing steps utilized in our study. For a comprehensive understanding and in-depth details of each step in the process, please refer to Section 4.5.1.

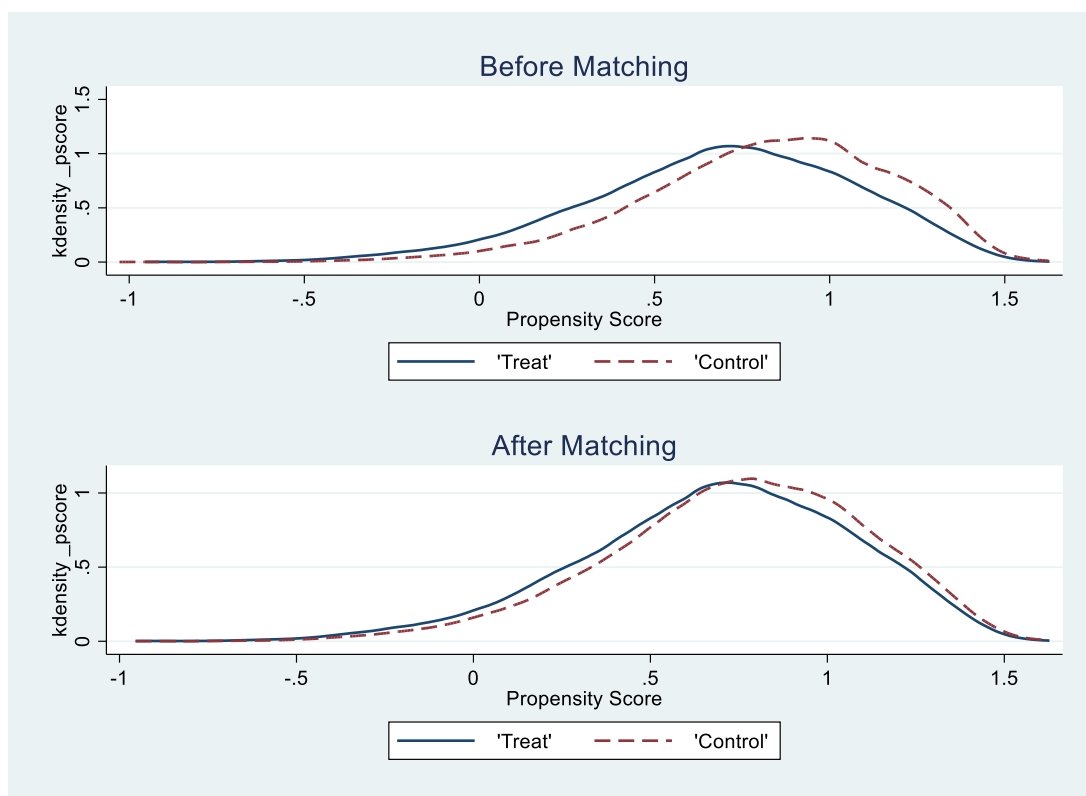
³⁴ According to Taylor and Pruiksma (2014), CBT-I is a psychotherapeutic approach that uses cognitive and behavioural therapy to address insomnia. The fundamental concept is to modify the patient's cognitive and behavioural sleep patterns through the implementation of various behavioural techniques and strategies aimed at enhancing sleep quality.

Figure 4.2 U-shaped relationship between OOP and Sleep Duration



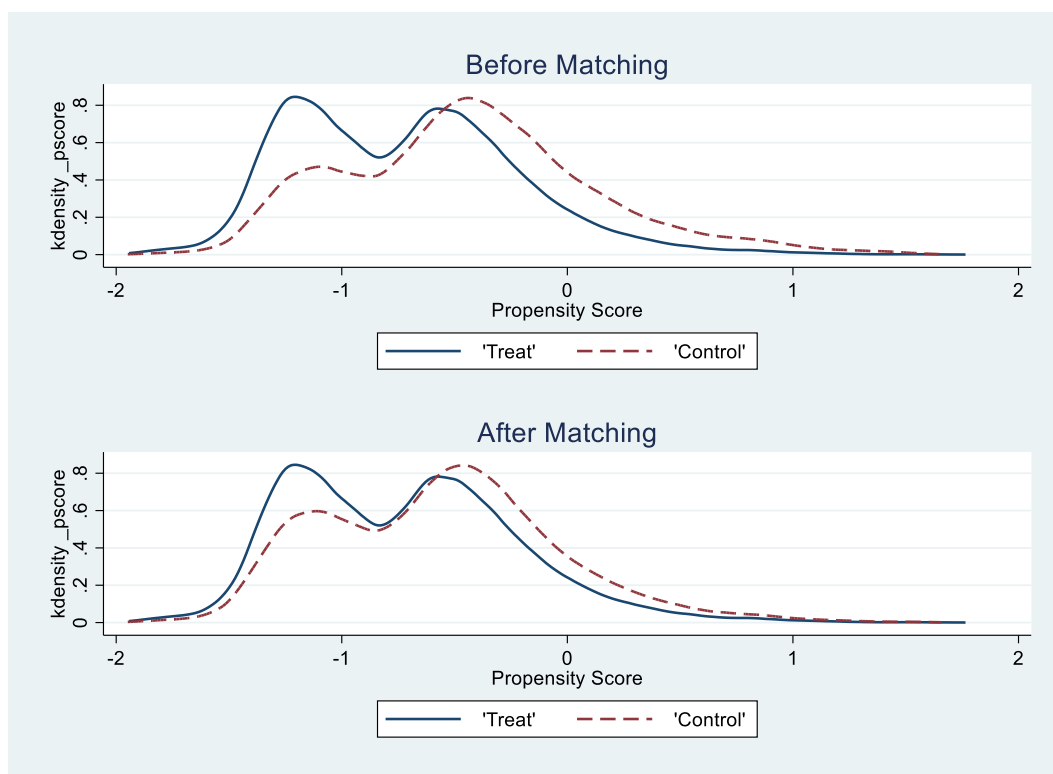
Note: The x-axis represents the duration of night sleep, measured in hours. The y-axis represents the logarithm of out-of-pocket medical expenses. Utilising a logarithmic scale for the y-axis enhances the effectiveness of visualising expenditure data that spans a wide range. This graph is derived from the data in column (1) of Table 4.3, allowing for a visual interpretation of the relationship described in the table.

Figure 4.3 Before and After Matching (Sleep Duration <6h)



Note: The graph above illustrates the distribution of propensity scores for both the treated group (sleep less than 6 hours) and the control group before and after the matching. The x-axis denotes the propensity score. The y-axis displays the kernel density estimate of the distribution of propensity scores. The upper panel depicts the initial disparity between the treated and control groups before matching, while the lower panel displays the enhanced convergence and equilibrium between the two groups after the matching.

Figure 4.4 Before and After Matching (Sleep Quality)



Note: The graph illustrates the distribution of propensity scores for both the treated group (those with good sleep quality) and the control group before and after the matching. The x-axis denotes the propensity score. The y-axis displays the kernel density estimate of the distribution of propensity scores. The upper panel depicts the initial disparity between the treated and control groups before matching, while the lower panel displays the enhanced convergence and equilibrium between the two groups after the matching.

Chapter 4 Tables

Table 4.1 Variables Definitions

VARIABLES	Definition
Medical Expenditure	
OOP Medical Expenditure	Continuous variable indicating the respondent's total OOP medical expenditure.
L_OOP Medical Expenditure	Continuous variable that represents the logarithm of out-of-pocket medical expenditures

Catastrophic Health Expenditure	Dummy variable equal to 1 if the respondent's OOP medical expenditure is greater than 40 percent of their household's capacity to pay, and 0 otherwise.
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Sleep Variables

Night Sleep Duration	Continuous variable indicating the average number of hours the respondent actually sleeps each night over the past month.
Night Sleep Duration sq	Square of Night Sleep Duration.
Good Sleep Quality	Dummy variable equal to 1 if the respondent has a good sleep quality, 0 otherwise.

Controls

Private Health Insurance	Dummy variable equal to 1 if the respondent is covered by Private Health Insurance, 0 otherwise.
URRMI	Dummy variable equal to 1 if the respondent is covered by the Urban and Rural Resident Medical Insurance (URRMI), 0 otherwise.
UEBMI	Dummy variable equal to 1 if the respondent is covered by the Urban Employee Basic Medical Insurance (UEBMI), 0 otherwise.
URBMI	Dummy variable equal to 1 if the respondent is covered by the Urban Resident Basic Medical Insurance (URBMI), 0 otherwise.
NRCMI	Dummy variable equal to 1 if the respondent is covered by the New Rural Cooperative Medical Insurance (NRCMI), 0 otherwise.
illiterate	Dummy variable equal to 1 if the respondent is illiterate, 0 otherwise.
primary	Dummy variable equal to 1 if the person has completed primary education, 0 otherwise.
secondary	Dummy variable equal to 1 if the individual has completed secondary school, 0 otherwise.
college	Dummy variable equal to 1 if the person has earned a college degree, 0 otherwise.
married	Dummy variable equal to 1 if the respondent is married, 0 otherwise.
chronics	Number of chronic diseases.
smoke	Dummy variable equal to 1 if the respondent currently smokes, 0 otherwise.
drink	Dummy variable equal to 1 if the respondent has consumed alcoholic beverages, such as beer, wine, or liquor this year, 0 otherwise.
ADLs	Number of limitations in basic activities of daily living.

IADLs	Number of limitations in instrumental activities of daily living.
work	Dummy variable equal to 1 if the respondent is now employed, and 0 if the respondent is currently unemployed or retired.
rural	Dummy variable equal to 1 if the respondent lives in the rural area, and 0 if the respondent lives in the urban area.
male	Dummy variable equal to 1 if the respondent is male, 0 otherwise
age	Continuous variable indicating the respondent's age.
Income	Average household income of the respondent, including labor income, capital gains, and government transfers.
Lincome	Logarithm of the average household income.

Mechanisms

Outpatient Frequency	Frequency of outpatient visits.
Inpatient Frequency	Frequency of inpatient visits.

Instrument

D_SunshineHour	Average number of sunshine hours at the city level.
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Table 4.2 Descriptive Statistics of all the Variables

VARIABLES	N	Mean	sd	min	max
Medical Expenditure					
OOP_Medical_Expenditure	57,023	1,633	5,697	0	47,025
I_OOP_Medical_Expenditure	57,023	1.937	3.463	0	10.76
Catastrophic_Health_Expenditure	56,642	0.107	0.310	0	1
Sleep Variables					
Night Sleep Duration	57,023	6.268	1.874	1	11
good_sleep_quality	55,120	0.650	0.477	0	1
Controls					
UEBMI	57,023	0.132	0.338	0	1
URBMI	57,023	0.0504	0.219	0	1
NRCMI	57,023	0.740	0.439	0	1
URRMI	57,023	0.0489	0.216	0	1
private_health_insurance	57,023	0.0746	0.263	0	1
Male	57,023	0.477	0.499	0	1
Age	57,023	60.98	9.648	45	118
Illiterate	57,023	0.253	0.435	0	1

Primary	57,023	0.556	0.497	0	1
Secondary	57,023	0.337	0.473	0	1
College	57,023	0.0223	0.148	0	1
Married	57,023	0.869	0.338	0	1
Chronics	57,023	1.660	1.621	0	13
Smoke	57,023	0.422	0.494	0	1
Drink	57,023	0.340	0.474	0	1
ADLs	57,023	0.369	0.984	0	6
IADLs	57,023	0.449	1.035	0	5
Work	57,023	0.657	0.475	0	1
Rural	57,023	0.611	0.487	0	1
Year	57,023	2,014	2.599	2,011	2,018
Income	57,023	11,454	15,756	0	104,676

Mechanisms

inpatient_frequency	57,004	0.204	0.692	0	25
outpatient_frequency	54,270	0.344	1.288	0	37

Instrument Variable

D_SunshineHour	57,022	5.407	1.252	2.642	8.433
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Note: OOP Medical Expenditure and Income are measured in Chinese Yuan.
Night_Sleep_Duration is measured in hours.

Table 4.3 Baseline Model Results (Sleep Duration)

	(1)	(2)	(3)	(4)
VARIABLES	L OOP Medical Expenditure	CHE (FE-LPM)	CHE (FE-LPM)	CHE (CRE-Probit)
night_sleep_duration	-0.182*** (-3.300)	-0.008 (-1.448)	-0.003** (-2.304)	-0.003*** (-4.164)
night_sleep_duration_sq	0.012*** (2.655)	0.000 (0.987)	-	-
Age	0.024* (1.827)	0.001 (0.400)	0.001 (0.400)	0.001 (0.522)
o.male	-	-	-	0.001 (0.220)
married	-0.345*** (-3.052)	-0.047*** (-3.996)	-0.047*** (-4.003)	-0.040*** (-4.042)
chronics	0.129***	-0.000	-0.000	0.018***

	(5.444)	(-0.139)	(-0.121)	(21.114)
lincome	0.024***	-0.003***	-0.003***	-0.003***
	(2.864)	(-3.666)	(-3.676)	(-3.843)
work	-0.446***	-0.035***	-0.035***	-0.031***
	(-8.272)	(-6.712)	(-6.721)	(-6.645)
UEBMI	0.230**	0.018*	0.018*	0.021**
	(2.204)	(1.911)	(1.908)	(1.994)
URBMI	0.194	-0.004	-0.004	-0.003
	(1.515)	(-0.380)	(-0.378)	(-0.235)
NRCMI	0.322***	-0.001	-0.001	0.000
	(3.468)	(-0.057)	(-0.066)	(0.026)
URRMI	0.266**	0.005	0.005	0.005
	(2.423)	(0.440)	(0.440)	(0.473)
private_health_insurance	0.062	0.007	0.007	0.007
	(0.866)	(1.091)	(1.087)	(1.018)
IADLs	0.240***	0.021***	0.021***	0.014***
	(8.534)	(7.253)	(7.286)	(6.990)
ADLs	0.161***	0.010***	0.010***	0.005**
	(5.452)	(3.078)	(3.098)	(2.337)
smoke	0.140	0.002	0.002	0.002
	(1.193)	(0.194)	(0.188)	(0.149)
drink	-0.343***	-0.029***	-0.029***	-0.028***
	(-5.814)	(-5.356)	(-5.365)	(-5.193)
college	0.182	0.007	0.008	-0.025**
	(0.722)	(0.374)	(0.381)	(-2.037)
illiterate	-0.016	0.004	0.004	0.001
	(-0.155)	(0.452)	(0.450)	(0.209)
primary	-0.060	0.003	0.003	0.003
	(-0.640)	(0.364)	(0.364)	(0.769)
secondary	-0.196*	-0.011	-0.011	-0.002
	(-1.858)	(-1.216)	(-1.207)	(-0.417)
o.rural	-	-	-	0.005
				(1.642)

U test	Pass	-	-	-
Extreme point	7.855	-	-	-
Left Slope	-0.159***	-	-	-
Right Slope	0.073**	-	-	-
N	57,023	56,642	56,642	56,642

Note: Coefficients obtained by estimating Equation (4-1) using a fixed effects model are displayed in columns and 3, while marginal effects obtained by estimating the same equation using a Probit CRE model are displayed in columns 2 and 4. The CRE model also includes means of time-varying variables. Their coefficients are not reported for brevity, but are available upon request. Year dummies are also included in all models. N is the number of observations. Definitions of all variables can be found in Table 4.1. Robust t-statistics are in parentheses. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

Table 4.4 Segmented Sleep Duration (<6h)

VARIABLES	(1) L_OOP	(2) CHE
Sleep_Duration_Dummy	0.176*** (4.031)	0.012*** (2.766)
age	0.024* (1.819)	0.001 (0.397)
o.male	-	-
married	-0.343*** (-3.032)	-0.046*** (-3.980)
chronics	0.130*** (5.492)	-0.000 (-0.116)
lincome	0.024*** (2.830)	-0.003*** (-3.677)
work	-0.447*** (-8.288)	-0.035*** (-6.715)
UEBMI	0.229** (2.192)	0.018* (1.905)
URBMI	0.192 (1.497)	-0.005 (-0.396)
NRCMI	0.322*** (3.467)	-0.000 (-0.053)
URRMI	0.264** (2.412)	0.005 (0.432)
private_health_insurance	0.060 (0.850)	0.007 (1.083)

IADLs	0.243*** (8.610)	0.021*** (7.286)
ADLs	0.162*** (5.489)	0.010*** (3.086)
smoke	0.139 (1.182)	0.002 (0.193)
drink	-0.345*** (-5.849)	-0.029*** (-5.371)
college	0.190 (0.750)	0.008 (0.391)
illiterate	-0.016 (-0.159)	0.004 (0.452)
primary	-0.059 (-0.631)	0.003 (0.371)
secondary	-0.193* (-1.824)	-0.011 (-1.203)
o.rural	-	-
N	57,023	56,642

Note: Coefficients obtained by estimating Equation (4-2) using a fixed effects model are displayed in columns 1 and 2. In this table, 'sleep_duration_dummy' is set to 1 to indicate individuals who sleep less than 6 hours and 0 otherwise. Year dummies are also included in all models. N is the number of observations. Robust t-statistics are in parentheses. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$

Table 4.5 Baseline Model (Sleep Quality)

VARIABLES	(1) L OOP (fixed effects)	(2) CHE (LPM)	(3) CHE (CRE-Probit)
good_sleep_quality	-0.249*** (-5.721)	-0.014*** (-3.464)	-0.022*** (-8.071)
age	0.022* (1.658)	0.001 (0.449)	0.001 (0.559)
o.male	-	-	0.003 (0.626)
married	-0.341*** (-2.910)	-0.049*** (-4.139)	-0.043*** (-4.171)
chronics	0.112*** (4.562)	-0.001 (-0.392)	0.017*** (19.778)

lincome	0.024*** (2.840)	-0.003*** (-3.613)	-0.003*** (-3.730)
work	-0.439*** (-8.037)	-0.035*** (-6.604)	-0.031*** (-6.474)
UEBMI	0.234** (2.193)	0.018* (1.905)	0.020* (1.957)
URBMI	0.237* (1.838)	-0.003 (-0.217)	-0.001 (-0.124)
NRCMI	0.327*** (3.479)	0.003 (0.373)	0.004 (0.433)
URRMI	0.271** (2.445)	0.005 (0.491)	0.005 (0.499)
private_health_insurance	0.049 (0.686)	0.006 (0.896)	0.006 (0.836)
IADLs	0.232*** (7.960)	0.020*** (6.785)	0.014*** (6.438)
ADLs	0.145*** (4.758)	0.008*** (2.624)	0.004* (1.957)
smoke	0.138 (1.138)	0.003 (0.227)	0.002 (0.152)
drink	-0.335*** (-5.613)	-0.028*** (-5.191)	-0.028*** (-5.064)
college	0.148 (0.564)	0.002 (0.107)	-0.025** (-2.006)
illiterate	0.004 (0.038)	0.007 (0.707)	0.002 (0.430)
primary	-0.058 (-0.606)	0.005 (0.507)	0.004 (1.001)
secondary	-0.182* (-1.680)	-0.011 (-1.185)	-0.001 (-0.202)
o.rural	-	-	0.005 (1.538)
N	55,692	55,348	55,348

Note: The results of the fixed effect model are displayed in column 1 and column 3, while the marginal effects of the CRE model are displayed in column 2 and column 4. The CRE model also includes means of time-varying variables. Year dummies are also included in all models. N is the number of observations. Definitions of all variables can be found in Table 4.1. Robust t-statistics are in parentheses. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

Table 4.6 GMM (Sleep Duration)

VARIABLES	(1) OOP	(2) CHE	(3) CHE
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night_sleep	-2.152** (0.921)	-0.108 (0.0970)	-0.0315** (0.0146)
night_sleep_sq	0.167** (0.0785)	0.00664 (0.00830)	-
age	0.0255 (0.0202)	0.00225 (0.00211)	0.00262 (0.00198)
male	1.948** (0.907)	-0.110 (0.0707)	-0.103 (0.0678)
married	0.144 (0.302)	0.0135 (0.0305)	0.0134 (0.0297)
chronics	0.345** (0.173)	0.0148 (0.0166)	0.0126 (0.0159)
lincome	-0.207 (0.145)	-0.0195** (0.00863)	-0.0203** (0.00829)
work	0.509 (0.766)	-0.0309 (0.0807)	-0.0101 (0.0725)
UEBMI	2.307 (1.604)	0.0637 (0.126)	0.0573 (0.122)
URBMI	1.558 (1.771)	0.356 (0.232)	0.321 (0.219)
NRCMI	2.691** (1.194)	0.115 (0.117)	0.0868 (0.109)
URRMI	1.248 (1.501)	-0.0875 (0.134)	-0.0897 (0.130)
private_health_insurance	0.192 (0.890)	0.122* (0.0639)	0.102* (0.0572)
IADLs	-0.691 (0.553)	-0.169*** (0.0576)	-0.148*** (0.0488)
ADLs	0.608 (0.588)	0.146** (0.0596)	0.139** (0.0568)
smoke	-2.114** (1.056)	0.176** (0.0797)	0.164** (0.0748)
drink	-1.958*** (0.734)	-0.0635 (0.0702)	-0.0726 (0.0666)
college	-0.924 (1.227)	0.0134 (0.0594)	0.0123 (0.0588)
illiterate	0.356 (0.435)	0.0280 (0.0435)	0.0260 (0.0424)
primary	0.529 (0.546)	-0.00305 (0.0554)	-0.00388 (0.0538)
secondary	1.085 (0.695)	0.0520 (0.0652)	0.0568 (0.0619)
rural	0.488 (1.152)	0.0188 (0.0344)	0.0221 (0.0334)

Hansen test P value	0.104	0.238	0.177
AR(1)	0.000***	0.000***	0.000***
AR(2)	0.136	0.601	0.681
N	57,022	56,642	56,642

Note: All independent and control variables are considered endogenous (with the exception of age and gender) and are instrumented using twice lagged values of themselves. In addition, we utilize daily average sunshine hours (D_SunshineHour) as an additional instrumental variable. Orthogonal deviations for handling missing data is applied. Year dummies are also included in all models. N is the number of observations. Definitions of all variables can be found in Table 4.1. Robust standard errors are in parentheses. The Hansen test is utilized to assess the appropriateness of the instruments in a model, with its null hypothesis stating that the instruments are valid. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

Table 4.7 GMM (Sleep Quality)

	(1)	(2)
VARIABLES	OOP	CHE
good_sleep_quality	-3.260*** (0.886)	-0.215*** (0.0730)
age	0.008 (0.0153)	-0.000 (0.0016)
male	1.557* (0.845)	0.0631 (0.0488)
married	0.224 (0.294)	-0.001 (0.0272)
chronics	0.295*** (0.0838)	0.005 (0.007)
lincome	-0.0825 (0.109)	0.002 (0.0117)
work	0.225 (0.701)	-0.055 (0.0432)
UEBMI	2.090* (1.268)	-0.059 (0.130)
URBMI	0.874 (1.377)	0.0164 (0.136)
NRCMI	2.237** (1.071)	-0.0343 (0.111)

URRMI	2.271 (1.383)	-0.145 (0.139)
private_health_insurance	-0.211 (0.719)	-0.006 (0.0598)
IADLs	-0.307 (0.370)	-0.0013 (0.0333)
ADLs	0.445 (0.397)	-0.0026 (0.0376)
smoke	-1.392 (1.079)	0.0029 (0.0409)
drink	-0.492 (0.970)	-0.0371 (0.0657)
college	-1.384* (0.773)	0.0512 (0.0911)
illiterate	-0.120 (0.399)	0.0405 (0.0756)
primary	-0.510 (0.326)	-0.0913* (0.0507)
secondary	0.328 (0.397)	0.0293 (0.0600)
rural	-1.494 (0.926)	-0.0313 (0.0830)
Hansen test P value	0.178	0.377
AR(1)	0.000***	0.000***
AR(2)	0.220	0.376
N	55,691	55,348

Note: All independent and control variables are considered endogenous (with the exception of age and gender) and are instrumented using twice lagged values of themselves. In addition, we utilize daily average sunshine hours (D_SunshineHour) as an additional instrumental variable. Orthogonal deviations for handling missing data is applied. Year dummies are also included in all models. N is the number of observations. Definitions of all variables can be found in Table 4.1. Robust standard errors are in parentheses. The Hansen test is utilized to assess the appropriateness of the instruments in a model, with its null hypothesis stating that the instruments are valid. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

Table 4.8 Logit Model for Estimating the Propensity Score (Sleep duration)

VARIABLES	(1) sleep_duration (<6 >8h)	(2) sleep_duration (<6h)	(3) sleep_duration (>8h)
<i>age_{it}</i>	0.017*** (12.647)	0.008*** (5.891)	0.017*** (9.617)
<i>gender_{it}</i>	-0.225*** (-7.054)	-0.415*** (-12.276)	0.299*** (6.723)
<i>married_{it-1}</i>	-0.211*** (-6.318)	-0.083** (-2.443)	-0.177*** (-4.168)
<i>chronics_{it-1}</i>	0.086*** (11.467)	0.136*** (17.787)	-0.073*** (-6.777)
<i>lincome_{it-1}</i>	-0.028*** (-6.275)	-0.030*** (-6.663)	-0.000 (-0.009)
<i>work_{it-1}</i>	-0.072*** (-2.782)	0.084*** (3.078)	-0.282*** (-7.900)
<i>UEBMI_{it-1}</i>	-0.165*** (-3.260)	-0.034 (-0.632)	-0.313*** (-4.118)
<i>URBMI_{it-1}</i>	-0.038 (-0.653)	0.049 (0.802)	-0.198** (-2.227)
<i>NRCMI_{it-1}</i>	0.061 (1.386)	0.016 (0.333)	0.082 (1.300)
<i>URRMI_{it-1}</i>	0.020 (0.258)	0.039 (0.487)	-0.044 (-0.394)
<i>private_health_insurance_{it-1}</i>	-0.085** (-2.081)	-0.071 (-1.638)	-0.066 (-1.087)
<i>IADLs_{it-1}</i>	0.137*** (9.875)	-0.018 (-1.290)	0.218*** (13.488)
<i>ADLs_{it-1}</i>	0.090*** (6.139)	0.119*** (8.382)	-0.055*** (-3.127)
<i>smoke_{it-1}</i>	-0.005 (-0.160)	0.004 (0.129)	-0.014 (-0.333)
<i>drink_{it-1}</i>	0.023 (0.937)	0.091*** (3.461)	-0.124*** (-3.513)
<i>college_{it-1}</i>	-0.047 (-0.602)	-0.147* (-1.705)	0.143 (1.176)
<i>illiterate_{it-1}</i>	0.098*** (3.115)	-0.150*** (-4.596)	0.399*** (9.285)
<i>primary_{it-1}</i>	-0.205*** (-6.384)	-0.168*** (-4.959)	-0.130*** (-2.744)
<i>secondary_{it-1}</i>	-0.028 (-0.927)	-0.027 (-0.856)	-0.061 (-1.336)
<i>rural_{it-1}</i>	-0.011	-0.009	-0.001

	(-0.441)	(-0.344)	(-0.025)
N	40,945	40,945	40,945

Note: N is the number of observations. Definitions of all variables can be found in Table 4.1.

Robust t-statistics are in parentheses. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

Table 4.9 Estimation on matched samples (Sleep Duration <6h)

VARIABLES	(1) L_OOP	(2) CHE
Sleep_Duration_Dummy	0.138** (2.408)	0.011** (1.990)
age	0.009 (0.531)	-0.001 (-0.369)
o.male	-	-
married	-0.458*** (-3.026)	-0.046*** (-2.946)
chronics	0.010 (0.364)	-0.006** (-2.288)
lincome	0.022** (2.054)	-0.003*** (-2.648)
work	-0.408*** (-5.799)	-0.033*** (-4.858)
UEBMI	0.291** (2.133)	0.034*** (2.756)
URBMI	0.291* (1.744)	0.002 (0.095)
NRCMI	0.442*** (3.905)	0.007 (0.594)
URRMI	0.413*** (3.234)	0.011 (0.834)
private_health_insurance	0.072 (0.782)	0.014 (1.600)
IADLs	0.278*** (7.697)	0.023*** (6.229)
ADLs	0.155*** (4.140)	0.009** (2.219)
smoke	0.122 (0.658)	0.024 (1.251)
drink	-0.397*** (-5.030)	-0.034*** (-4.608)

college	0.132 (0.365)	0.033 (1.146)
illiterate	0.131 (1.034)	0.023* (1.864)
primary	0.024 (0.209)	0.018 (1.605)
secondary	-0.212 (-1.506)	-0.017 (-1.399)
o.rural	-	-
N	38,159	37,374

Note: The treatment group in this table indicates those who sleep less than 6 hours. Year dummies are included in all models. N is the number of observations. Robust t-statistics are in parentheses. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$

Table 4.10 Logit Model for Estimating the Propensity Score (Sleep Quality)

VARIABLES	(1) all
age_{it}	0.004*** (3.057)
$gender_{it}$	0.654*** (18.506)
$married_{it-1}$	0.135*** (3.749)
$chronics_{it-1}$	-0.165*** (-20.435)
$lincome_{it-1}$	0.029*** (6.126)
$work_{it-1}$	-0.023 (-0.808)
$UEBMI_{it-1}$	-0.059 (-1.053)
$URBMI_{it-1}$	0.030 (0.457)
$NRCMI_{it-1}$	-0.102** (-2.066)
$URRMI_{it-1}$	-0.096 (-1.145)
$private_health_insurance_{it-1}$	0.170*** (3.780)
$IADLs_{it-1}$	-0.121*** (-7.967)

$ADLs_{it-1}$	-0.149*** (-9.469)
$smoke_{it-1}$	-0.071** (-2.136)
$drink_{it-1}$	0.062** (2.280)
$college_{it-1}$	0.365*** (3.855)
$illiterate_{it-1}$	0.014 (0.405)
$primary_{it-1}$	0.108*** (3.098)
$secondary_{it-1}$	0.014 (0.437)
$rural_{it-1}$	0.003 (0.125)
N	37,722

Note: N is the number of observations. Definitions of all variables can be found in Table 4.1. Robust t-statistics are in parentheses. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

Table 4.11 Estimation of the matched sample (Sleep Quality)

VARIABLES	(1) L_OOP	(2) CHE
Good Sleep Quality	-0.238*** (-4.076)	-0.015*** (-2.770)
age	0.006 (0.304)	-0.001 (-0.459)
o.male	-	-
married	-0.504*** (-3.138)	-0.052*** (-3.294)
chronics	-0.008 (-0.292)	-0.008*** (-2.775)
lincome	0.024** (2.082)	-0.002* (-1.716)
work	-0.404*** (-5.492)	-0.035*** (-4.864)
UEBMI	0.181 (1.260)	0.025** (2.019)

URBMI	0.330* (1.887)	-0.003 (-0.209)
NRCMI	0.402*** (3.341)	0.010 (0.847)
URRMI	0.387*** (2.869)	0.012 (0.887)
private_health_insurance	0.059 (0.609)	0.017* (1.909)
IADLs	0.271*** (6.766)	0.024*** (5.804)
ADLs	0.104** (2.485)	0.007 (1.507)
smoke	0.134 (0.668)	0.022 (1.077)
drink	-0.371*** (-4.532)	-0.031*** (-4.095)
college	0.039 (0.100)	0.035 (1.112)
illiterate	0.096 (0.706)	0.009 (0.730)
primary	0.026 (0.214)	0.015 (1.290)
secondary	-0.228 (-1.517)	-0.021 (-1.574)
o.rural	-	-
N	35,335	35,138

Note: Year dummies are included in all models. N is the number of observations. Robust t-statistics are in parentheses. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$

Table 4.12 Mediation effect (sleep duration < 6h)

Variables	Outpatient		Inpatient	
	(1) OOP	(2) CHE	(3) OOP	(4) CHE
Step 1 Coefficient (α_1)	0.170*** (0.043)	0.009** (0.004)	0.177*** (0.043)	0.012*** (0.004)
Step 2 Coefficient (β_1)	0.053*** (0.017)	0.051*** (0.017)	0.010 (0.008)	0.010 (0.008)
Step 3 Coefficient (γ_1)	1.087***	0.073***	2.313***	0.138***

	(0.013)	(0.001)	(0.024)	(0.002)
Step 3 Coefficient (γ_2)	0.112***	0.005	0.153***	0.010***
	(0.039)	(0.004)	(0.034)	(0.004)
Indirect effect	0.0579***	0.0037**	0.0240	0.0014
Sobel test statistic	3.147***	2.977***	1.235	1.197
IDind FE	Yes	Yes	Yes	Yes
wave FE	Yes	Yes	Yes	Yes
Add Control	Yes	Yes	Yes	Yes
N	54,270	53,900	57,004	56,623

Note: The Step 1 Coefficient (α_1) is derived from Equation (4-5), the Step 2 Coefficient (β_1) is derived from Equation (4-6), and the Step 3 Coefficients (γ_1, γ_2), from Equation (4-7). N is the number of observations. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$

Table 4.13 Mediation effect (sleep quality)

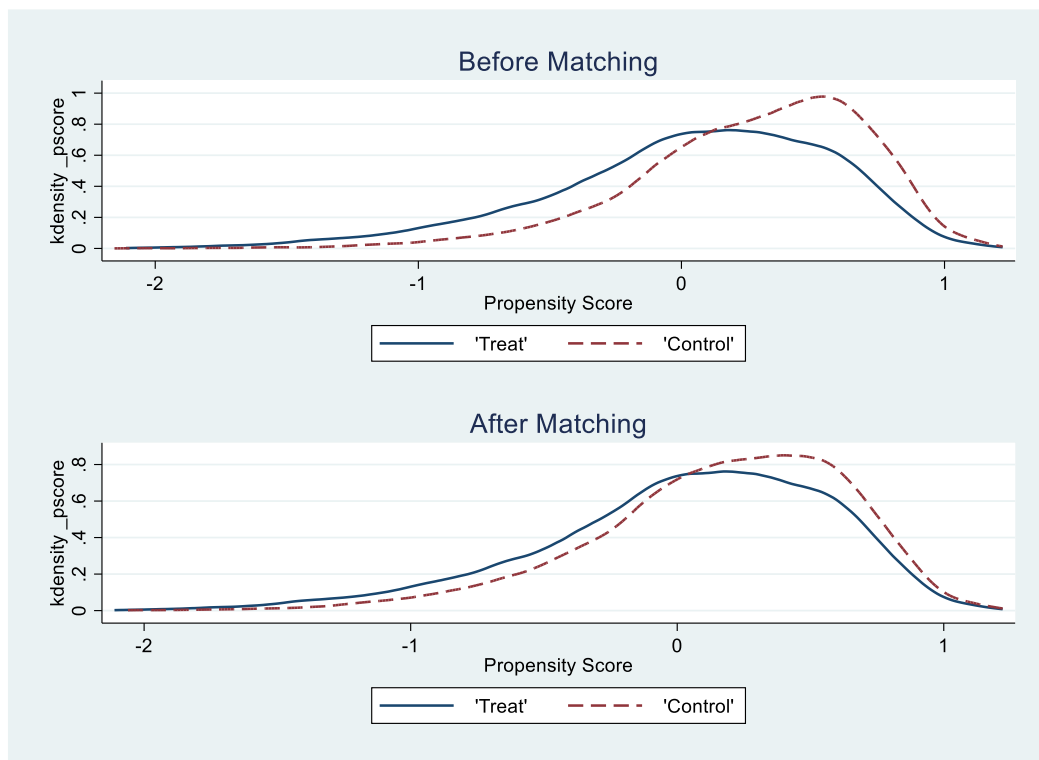
	Outpatient		Inpatient	
	(1)	(2)	(3)	(4)
Variables	OOP	CHE	OOP	CHE
Step 1 Coefficient (α_1)	-0.228***	-0.014***	-0.249***	-0.014***
1)	(0.042)	(0.004)	(0.042)	(0.004)
Step 2 Coefficient (β_1)	-0.071***	-0.070***	-0.016**	-0.016**
1)	(0.017)	(0.017)	(0.008)	(0.008)
Step 3 Coefficient (γ_1)	1.088***	0.072***	2.425***	0.143***
1)	(0.012)	(0.001)	(0.025)	(0.007)
Step 3 Coefficient (γ_2)	-0.151***	-0.009**	-0.210***	-0.012***
2)	(0.029)	(0.004)	(0.037)	(0.003)
Indirect effect	-0.0769***	-0.005***	-0.0389**	-0.0023**
Sobel test statistic	-4.246***	-4.183***	-2.044**	-2.047**
IDind FE	Yes	Yes	Yes	Yes
wave FE	Yes	Yes	Yes	Yes
Add Control	Yes	Yes	Yes	Yes

N	53,182	52,846	55,671	55,327
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Note: The specific implementation of the Mediation effect model is described in the Methodology section. Step 1 Coefficient (α_1) is driven from Equation (4-5), Step 2 Coefficient (β_1) is driven from Equation (4-6), and Step 3 Coefficients (γ_1 , γ_2) are driven from Equation (4-7). N is the number of observations. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

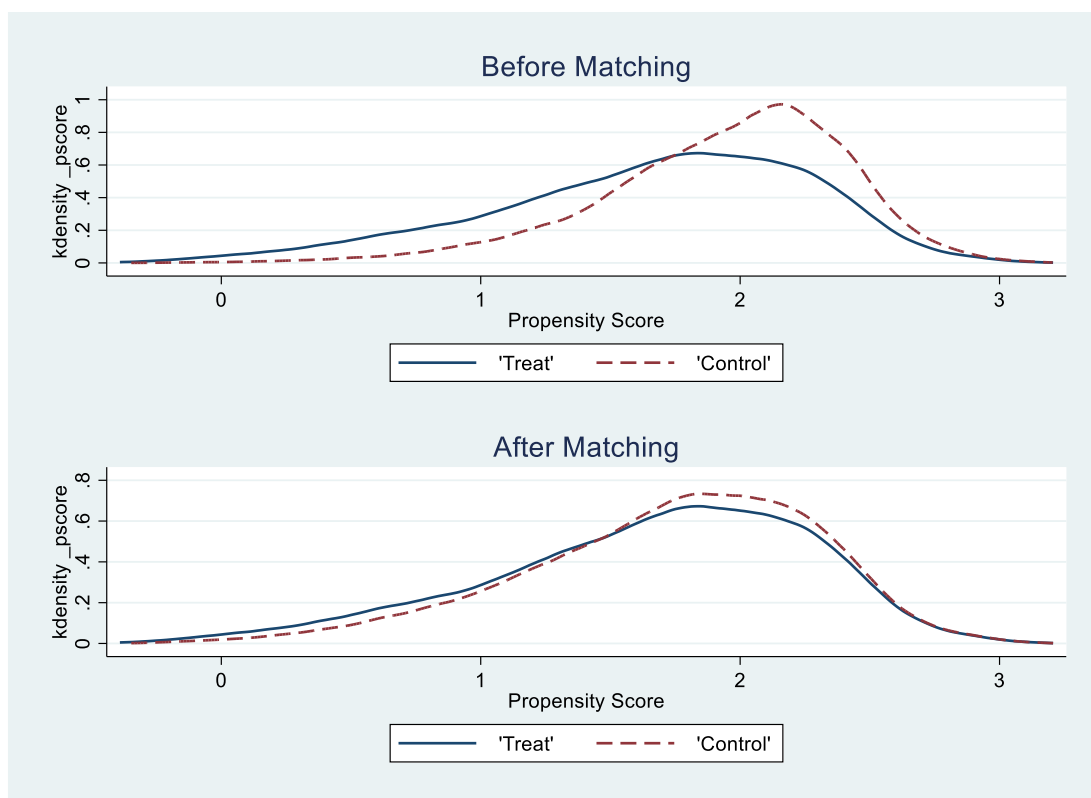
Appendix for Chapter 4

Figure A4.5 Before and After Matching (sleep duration <6h, >8h)



Note: The graph above illustrates the distribution of propensity scores for both the treated group (sleep less than 6 hours or more than 8 hours) and the control group before and after the matching. The x-axis denotes the propensity score. The y-axis displays the kernel density estimate of the distribution of propensity scores. The upper panel depicts the initial disparity between the treated and control groups before matching, while the lower panel displays the enhanced convergence and equilibrium between the two groups after the matching.

Figure A4.6 Before and After Matching (sleep duration>8h)



Note: The graph above illustrates the distribution of propensity scores for both the treated group (sleep more than 8 hours) and the control group before and after the matching. The x-axis denotes the propensity score. The y-axis displays the kernel density estimate of the distribution of propensity scores. The upper panel depicts the initial disparity between the treated and control groups before matching, while the lower panel displays the enhanced convergence and equilibrium between the two groups after the matching.

Table A4.14 Segmented Sleep Duration (<6h or >8h)

VARIABLES	(1) L_OOP	(2) CHE
Sleep_Duration_Dummy	0.123*** (3.178)	0.006 (1.569)
age	0.024* (1.825)	0.001 (0.404)
o.male	-	-
married	-0.346*** (-3.058)	-0.047*** (-4.010)

chronics	0.131*** (5.527)	-0.000 (-0.083)
lincome	0.024*** (2.832)	-0.003*** (-3.674)
work	-0.447*** (-8.283)	-0.035*** (-6.713)
UEBMI	0.230** (2.199)	0.018* (1.914)
URBMI	0.192 (1.498)	-0.005 (-0.391)
NRCMI	0.323*** (3.486)	-0.000 (-0.042)
URRMI	0.264** (2.410)	0.005 (0.439)
private_health_insurance	0.061 (0.857)	0.007 (1.088)
IADLs	0.243*** (8.629)	0.021*** (7.308)
ADLs	0.163*** (5.514)	0.010*** (3.113)
smoke	0.140 (1.194)	0.002 (0.202)
drink	-0.344*** (-5.835)	-0.029*** (-5.353)
college	0.187 (0.740)	0.008 (0.376)
illiterate	-0.017 (-0.170)	0.004 (0.446)
primary	-0.061 (-0.645)	0.003 (0.364)
secondary	-0.195* (-1.849)	-0.012 (-1.225)
o.rural	-	-

N	57,023	56,642
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Note: Coefficients obtained by estimating Equation (4-2) using a fixed effects model are displayed in columns 1 and 2. In this table, 'sleep_duration_dummy' is set to 1 to indicate individuals who sleep less than 6 hours or more than 8 hours, and 0 otherwise. Year dummies are also included in all models. N is the number of observations. Robust t-statistics are in parentheses. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

Table A4.15 Segmented sleep duration (>8h)

VARIABLES	(1) L_OOP	(2) CHE
Sleep_Duration_Dummy	-0.049 (-0.746)	-0.010 (-1.496)
age	0.025* (1.843)	0.001 (0.412)
o.male	-	-
married	-0.354*** (-3.128)	-0.047*** (-4.048)
chronics	0.132*** (5.567)	-0.000 (-0.070)
lincome	0.024*** (2.833)	-0.003*** (-3.675)
work	-0.447*** (-8.284)	-0.035*** (-6.715)
UEBMI	0.233** (2.224)	0.018* (1.930)
URBMI	0.196 (1.529)	-0.004 (-0.367)
NRCMI	0.323*** (3.474)	-0.001 (-0.056)
URRMI	0.269** (2.456)	0.005 (0.470)
private_health_insurance	0.061 (0.853)	0.007 (1.084)
IADLs	0.245*** (8.690)	0.021*** (7.338)
ADLs	0.165*** (5.596)	0.010*** (3.153)
smoke	0.142 (1.206)	0.002 (0.205)
drink	-0.342*** (-5.803)	-0.029*** (-5.336)
college	0.180 (0.714)	0.007 (0.360)
illiterate	-0.016 (-0.158)	0.004 (0.458)
primary	-0.060 (-0.636)	0.003 (0.374)
secondary	-0.196* (-1.858)	-0.011 (-1.218)

o.rural

-

-

N

57,023

56,642

Note: Coefficients obtained by estimating Equation (4-2) using a fixed effects model are displayed in columns 1 and 2. In this table, 'sleep_duration_dummy' is set to 1 to indicate individuals who sleep more than 8 hours, and 0 otherwise. Year dummies are also included in all models. N is the number of observations. Robust t-statistics are in parentheses. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$

Table A4.16 Balance test (Sleep duration:<6h or >8h)

Variable	Match	Mean	Mean	%Bias	%Bias
Age	U	63.973	61.199	29.0	-
	M	63.973	63.849	1.3	95.5
male	U	0.4271	0.51879	-18.4	-
	M	0.4271	0.42914	-0.4	97.8
married	U	0.81258	0.88954	-21.7	-
	M	0.81258	0.82296	-2.9	86.5
chronics	U	1.9842	1.6081	22.4	-
	M	1.9842	1.962	1.3	94.1
lincome	U	7.7088	8.2158	-20.5	-
	M	7.7088	7.9757	-10.8	47.4
work	U	0.5887	0.67193	-17.3	
	M	0.5887	0.60221	-2.8	83.8
UEBMI	U	0.10376	0.14344	-12.1	
	M	0.10376	0.10683	-0.9	92.3
URBMI	U	0.04443	0.0487	-2.0	-
	M	0.04443	0.04474	-0.1	92.6
NRCMI	U	0.74849	0.71518	7.5	-
	M	0.74849	0.74995	-0.3	95.6
URRMI	U	0.06031	0.05683	1.5	-
	M	0.06031	0.05824	0.9	40.7

private_health_insuranc	U	0.06873	0.07921	-4.0	-
	M	0.06873	0.07345	-1.8	55.0
IADLs	U	0.74152	0.33353	36.0	-
	M	0.74152	0.56557	15.5	56.9
ADLs	U	0.61786	0.27438	31.6	-
	M	0.61786	0.46829	13.8	56.5
smoke	U	0.40941	0.41134	-10.3	-
	M	0.40941	0.40534	-0.4	96.2
drink	U	0.30237	0.35904	-12.1	-
	M	0.30237	0.29432	1.7	85.8
college	U	0.01391	0.02429	-7.6	-
	M	0.01391	0.01436	-0.3	95.6
illiterate	U	0.32972	0.21328	26.4	-
	M	0.32972	0.32768	0.5	98.2
primary	U	0.45951	0.6032	-29.1	-
	M	0.45951	0.46669	-1.5	95.0
secondary	U	0.25937	0.3772	-25.5	-
	M	0.25937	0.26221	-0.6	97.6
rural	U	0.64548	0.61091	7.2	-
	M	0.64548	0.64782	-0.5	93.2
MeanBias	U	17.1			
	M	2.9			
LR chi2	U	2533.33***			
	M	294.52***			

Note: This table presents balancing tests for sleep duration less than 6h and more than 8h. "Match Status" indicates whether the data is before matching (U for Unmatched) or after matching (M for Matched). The means for both the treated and control groups are shown for each variable. "%Bias" indicates the percentage bias between the treated and control groups, and "%Bias Reduction" shows the reduction in bias post-matching. The decreased LR chi2 value in the matched sample also confirms that covariate balance has significantly improved after matching.

Table A4.17 Balance Test (Sleep Duration <6h)

Variable	Matc	Mean	Mean	%Bias	%Bias
age	U	63.327	62.071	13.1	-

	M	63.327	63.433	-1.1	91.6
male	U	0.40748	0.50929	-20.5	-
	M	0.40748	0.40641	0.2	98.9
married	U	0.82275	0.86901	-12.8	-
	M	0.82275	0.83326	-2.9	77.3
lincome	U	2.1151	1.6224	28.8	-
	M	2.1151	1.9737	8.3	71.3
work	U	7.8891	8.027	-5.6	-
	M	7.8891	7.8813	0.3	94.3
UEBMI	U	0.60741	0.64602	-8	-
	M	0.60741	0.59453	2.7	66.6
URBMI	U	0.11005	0.13241	-6.9	-
	M	0.11005	0.11443	-1.3	80.4
NRCMI	U	0.04793	0.04619	0.8	-
	M	0.04793	0.05	-1	-18.9
URRMI	U	0.74003	0.72604	3.2	-
	M	0.74003	0.74796	-1.8	43.4
private_health_insuranc	U	0.0629	0.05631	2.8	-
	M	0.0629	0.05377	3.9	-38.5
IADLs	U	0.0719	0.07557	-1.4	-
	M	0.0719	0.07232	-0.2	88.7
ADLs	U	0.66405	0.4526	18.3	-
	M	0.66405	0.62236	3.6	80.3
smoke	U	0.59382	0.35524	21.4	-
	M	0.59382	0.50127	8.3	61.2
drink	U	0.39481	0.45717	-12.6	-
	M	0.39481	0.39598	-0.2	98.1
college	U	0.30942	0.34431	-7.4	-
	M	0.30942	0.29074	4	46.4
illiterate	U	0.01384	0.02203	-6.2	-
	M	0.01384	0.01506	-0.9	85
primary	U	0.29985	0.2512	10.9	-
	M	0.29985	0.30412	-1	91.2

secondary	U	0.48117	0.56359	-16.6	-
	M	0.48117	0.48544	-0.9	94.8
rural	U	0.27241	0.34694	-16.2	-
	M	0.27241	0.28311	-2.3	85.6
MeanBias	U	10.8			
	M	2.3			
LR chi2	U	1360.19***			
	M	111.70***			

Note: This table presents a balance test for participants with a sleep duration of less than 6 hours. "Match Status" indicates whether the data is before matching (U for Unmatched) or after matching (M for Matched). The means for both the treated and control groups are shown for each variable. "%Bias" indicates the percentage bias between the treated and control groups, and "%Bias Reduction" shows the reduction in bias post-matching. The decreased LR chi2 value in the matched sample also confirms that covariate balance has significantly improved after matching.

Table A4.18 Balance Test (Sleep Duration >8h)

Variable	Matc	Mean	Mean	%Bias	%Bias
age	U	65.474	61.987	33.8	-
	M	65.474	65.363	1.1	96.8
gender	U	0.47248	0.47754	-1	-
	M	0.47248	0.45797	2.9	-187
married	U	0.78885	0.86469	-20.1	-
	M	0.78885	0.79934	-2.8	86.2
chronics	U	1.6778	1.7963	-7.2	-
	M	1.6778	1.8491	-10.4	-44.6
lincome	U	7.2913	8.0949	-30.6	-
	M	7.2913	7.8249	-20.3	33.6
work	U	0.54526	0.64801	-21.1	-
	M	0.54526	0.56712	-4.5	78.7
UEBMI	U	0.08879	0.13128	-13.6	-
	M	0.08879	0.09556	-2.2	84.1
URBMI	U	0.03621	0.0484	-6.1	-

	M	0.03621	0.03919	-1.5	75.5
NRCMI	U	0.76856	0.72421	10.2	-
	M	0.76856	0.75893	2.2	78.3
URRMI	U	0.05422	0.05904	-2.1	-
	M	0.05422	0.0584	-1.8	13.2
private_health_insuranc	U	0.06133	0.07662	-6	-
	M	0.06133	0.07176	-4.1	31.8
IADLs	U	0.92416	0.45646	35.4	-
	M	0.92416	0.71256	16	54.8
ADLs	U	0.67398	0.39322	22.6	-
	M	0.67398	0.58611	7.1	68.7
smoke	U	0.44356	0.43614	1.5	-
	M	0.44356	0.43215	2.3	-53.8
drink	U	0.28592	0.34073	-11.8	-
	M	0.28592	0.28924	-0.7	93.9
college	U	0.01407	0.02065	-5	-
	M	0.01407	0.013	0.8	83.7
illiterate	U	0.39925	0.24543	33.4	-
	M	0.39925	0.40007	-0.2	99.5
primary	U	0.40905	0.5579	-30.1	-
	M	0.40905	0.41165	-0.5	98.3
secondary	U	0.22911	0.33839	-24.4	-
	M	0.22911	0.23352	-1	96
MeanBias (Average Bias)	U	16.3			
	M	4.3			
LR chi2	U	1524.7***			
	M	193.27***			

Note: This table presents a balance test for participants with sleep duration more than 8 hours. "Match Status" indicates whether the data is before matching (U for Unmatched) or after matching (M for Matched). The means for both the treated and control groups are shown for each variable. "%Bias" indicates the percentage bias between the treated and control groups, and "%Bias Reduction" shows the reduction in bias post-matching. The decreased LR chi2 value in the matched sample also confirms that covariate balance has significantly improved after matching.

Table A4.19 PSM (Sleep Duration <6h or >8h)

VARIABLES	(1) L_OOP	(2) CHE
Sleep_Duration_Dummy	0.142*** (2.855)	0.011** (2.182)
age	0.009 (0.521)	-0.001 (-0.376)
o.male	-	-
married	-0.460*** (-3.042)	-0.046*** (-2.963)
chronics	0.010 (0.374)	-0.006** (-2.276)
lincome	0.023** (2.126)	-0.003*** (-2.618)
work	-0.408*** (-5.797)	-0.033*** (-4.855)
UEBMI	0.295** (2.172)	0.034*** (2.763)
URBMI	0.291* (1.742)	0.001 (0.089)
NRCMI	0.445*** (3.928)	0.007 (0.599)
URRMI	0.413*** (3.237)	0.011 (0.828)
private_health_insurance	0.069 (0.745)	0.014 (1.611)
IADLs	0.277*** (7.677)	0.023*** (6.226)
ADLs	0.155*** (4.144)	0.009** (2.218)
smoke	0.122 (0.654)	0.024 (1.252)
drink	-0.393*** (-4.978)	-0.034*** (-4.595)
college	0.133 (0.370)	0.033 (1.146)
illiterate	0.129 (1.018)	0.023* (1.846)
primary	0.023 (0.199)	0.018 (1.599)
secondary	-0.215 (-1.528)	-0.018 (-1.421)

o.rural	-	-
N	38,162	37,374

Note: The treatment group in this table indicates those who sleep more than 8 hours or less than 6 hours. Year dummies are included in all models. N is the number of observations. Robust t-statistics are in parentheses. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$

Table A4.20 PSM (Sleep Duration >8h)

VARIABLES	(1) L_OOP	(2) CHE
Sleep_Duration_Dummy	0.071 (0.980)	0.004 (0.524)
age	0.009 (0.540)	-0.001 (-0.358)
o.male	-	-
married	-0.472*** (-3.118)	-0.046*** (-2.973)
chronics	0.011 (0.407)	-0.006** (-2.265)
lincome	0.023** (2.131)	-0.003*** (-2.664)
work	-0.406*** (-5.764)	-0.033*** (-4.842)
UEBMI	0.299** (2.201)	0.034*** (2.772)
URBMI	0.304* (1.824)	0.002 (0.109)
NRCMI	0.447*** (3.944)	0.007 (0.603)
URRMI	0.418*** (3.275)	0.011 (0.843)
private_health_insurance	0.069 (0.746)	0.014* (1.646)
IADLs	0.279*** (7.740)	0.024*** (6.280)
ADLs	0.158*** (4.214)	0.009** (2.249)
smoke	0.121 (0.647)	0.024 (1.250)
drink	-0.388*** (-4.918)	-0.034*** (-4.601)

college	0.133 (0.373)	0.033 (1.153)
illiterate	0.130 (1.024)	0.023* (1.856)
primary	0.023 (0.201)	0.018 (1.605)
secondary	-0.218 (-1.554)	-0.018 (-1.438)
o.rural	-	-

N	38,173	37,387
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Note: The treatment group in this table indicates those who sleep more than 8 hours. Year dummies are included in all models. N is the number of observations. Robust t-statistics are in parentheses. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

Table A4.21 Balance Test (Sleep Quality)

Variable	Match	Mean	Mean	%Bias	%Bias
age	U	61.809	62.347	-5.9	-
	M	61.809	61.826	-0.2	96.7
male	U	0.54066	0.36288	36.3	-
	M	0.54066	0.54716	-1.3	96.3
married	U	0.88162	0.83443	13.6	-
	M	0.88162	0.87185	2.8	79.3
lincome	U	1.559	2.1356	-34.3	-
	M	1.559	1.7122	-9.1	73.4
work	U	8.1347	7.8616	11.3	-
	M	8.1347	8.1023	1.3	88.2
UEBMI	U	0.6729	0.61642	11.8	-
	M	0.6729	0.65153	4.5	62.2
URBMI	U	0.13639	0.10444	9.8	-
	M	0.13639	0.13957	-1	90
NRCMI	U	0.04814	0.04431	1.8	-
	M	0.04814	0.04643	0.8	55.4
URRMI	U	0.71918	0.75141	-7.3	-

	M	0.71918	0.71343	1.3	82.2
private_health_insurance	U	0.05773	0.06171	-1.7	-
	M	0.05773	0.06021	-1	37.7
IADLs	U	0.07767	0.07016	2.9	-
	M	0.07767	0.08007	-0.9	67.9
ADLs	U	0.31087	0.66395	-34.2	-
	M	0.31087	0.4812	-16.5	51.8
smoke	U	0.25217	0.60291	-34.5	-
	M	0.25217	0.4225	-16.8	51.4
drink	U	0.47709	0.36326	23.2	-
	M	0.47709	0.48398	-1.4	93.9
college	U	0.3734	0.27703	20.7	-
	M	0.3734	0.36636	1.5	92.7
illiterate	U	0.02308	0.0112	9.2	-
	M	0.02308	0.02046	2	77.9
primary	U	0.22549	0.30448	-18	-
	M	0.22549	0.22436	0.3	98.6
secondary	U	0.58647	0.48133	21.2	-
	M	0.58647	0.5802	1.3	94
rural	U	0.36015	0.27521	18.3	-
	M	0.36015	0.35665	0.8	95.9
MeanBias (Average Bias)	U	16.1			
	M	3.3			
LR chi2	U	2728.51***			
	M	576.22***			

Note: The table shows a balance test for the propensity score matched groups based on good sleep quality." Match Status" indicates whether the data is before matching (U for Unmatched) or after matching (M for Matched). The means for both the treated and control groups are shown for each variable. "%Bias" indicates the percentage bias between the treated and control groups, and "%Bias Reduction" shows the reduction in bias post-matching. The decreased LR chi2 value in the matched sample also confirms that covariate balance has significantly improved after matching.

Table A4.22 Mediation effect (sleep duration<6h or >8h)

	Outpatient		Inpatient	
	(1)	(2)	(3)	(4)
Variables	OOP	CHE	OOP	CHE
Step 1 Coefficient (α_1)	0.128*** (0.039)	0.004 (0.004)	0.124*** (0.038)	0.006* (0.004)
Step 2 Coefficient (β_1)	0.039** (0.015)	0.038*** (0.015)	0.007 (0.008)	0.007 (0.008)
Step 3 Coefficient (γ_1)	1.087*** (0.013)	0.073*** (0.001)	2.313*** (0.024)	0.139*** (0.002)
Step 3 Coefficient (γ_2)	0.086*** (0.035)	0.001 (0.003)	0.108*** (0.034)	0.005 (0.004)
Indirect effect	0.0423***	0.0027**	0.0151	0.0009
Sobel test statistic	2.578***	2.487***	0.8716	0.8689
Control	Yes	Yes	Yes	Yes
IDind FE	Yes	Yes	Yes	Yes
wave FE	Yes	Yes	Yes	Yes
N	54,270	53,900	57,004	56,623

Note: The specific implementation of the Mediation effect model is described in the Methodology section. Step 1 Coefficient (α_1) is derived from Equation (4-5), Step 2 Coefficient (β_1) is derived from Equation (4-6), and Step 3 Coefficients (γ_1 , γ_2) are derived from Equation (4-7). N is the number of observations. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

Chapter 5 Conclusion

5.1. Summary

Investigating the effects of health insurance on elderly mental health, children's healthcare utilization, and the influence of sleep patterns on medical expenses is essential, especially in light of the significant reforms in China's healthcare and insurance systems. Understanding these relationships helps policymakers to evaluate the effectiveness of current policies and make policy adjustments based on empirical evidence. This will help improve insurance policy outcomes and enhance the allocation of healthcare resources.

In Chapter 2, using data taken from the CHARLS over the period 2011 to 2018, we explore the impact of health insurance on mental health among middle-aged and elderly people. We observe that 96.5% of the elderly are insured, with 95.89% covered by public insurance and 7.45% having private health insurance. The findings show that health insurance promotes mental health, especially through UEBMI, followed by URBMI, while NRCMI has no significant effect. People with both public and private health insurance are more likely to have good mental health than those with only public health insurance. Switching from NRCMI or URBMI to UEBMI, or from NRCMI to URBMI, is associated with better mental health. However, switching from UEBMI to URBMI is not beneficial to achieving good mental health. In addition, results also show that middle-aged and older adults whose insurance types have been combined into the URRMI are more likely to have good mental health.

In Chapter 3, based on data taken from the CFPS over the period 2010 to 2020, we observe that 74.7% of children are insured, with 69.4% participating in public health insurance and 15.9% having private coverage. We find that children with health insurance demonstrate a higher likelihood and frequency of healthcare utilization compared to uninsured children. This suggests that health insurance improves access to healthcare. In addition, this effect may also be influenced by moral hazard, as insured individuals may use more healthcare services or rely less on preventive measures due to reduced out-of-pocket costs. To address potential endogeneity issues caused by adverse selection, we employ the Control Function (CF) approach, using provincial-level health insurance participation rates as instruments. Additionally, those with public insurance are more likely to use healthcare services than those with private insurance. Furthermore, the URRMI merger policy is linked to increased healthcare utilization among children. Finally, Inequality in healthcare access is much smaller among insured children compared to uninsured ones.

In Chapter 4, we investigate the relationship between sleep and medical expenditure among middle-aged and elderly individuals using data from the CHARLS over the period 2011-2018. The results show a U-shaped relationship between night sleep duration and OOP medical expenses. The slope of the U-shape is notably steeper on the left and slower on the right, indicating that sleep deprivation plays a more significant role in the increase of medical expenses than excessive sleep. The U-shaped curve identifies approximately 7.86 hours of nightly sleep as the turning point where OOP medical expenditure is minimized. Specifically, sleeping less than 6 hours is linked to significantly higher OOP medical expenses both in the full sample and in matched samples. In

addition, longer sleep duration and better sleep quality are associated with a lower probability of incurring catastrophic health expenditure (CHE). Finally, we highlight the mediating roles of the frequency of outpatient visits and hospitalizations in the link between sleep and medical expenses, with outpatient visits having a more pronounced mediating effect.

5.2. Policy Implications

Promoting Equality in Public Health Insurance

Our research reveals significant disparities between China's public health insurance programs. UEBMI offers the highest reimbursement rates, while URBMI provides moderate benefits, and NRCMI offers the lowest. In Chapter 2, we find that UEBMI and URBMI have a significant positive effect on the mental health of middle-aged and older individuals, with UEBMI having the greatest impact. However, NRCMI has no significant effects on mental health. This also indicates potential disparities in coverage benefits between different health insurance programs.

Furthermore, Chapters 2 and 3 consistently validate the effectiveness of the Urban and Rural Resident Medical Insurance (URRMI) policy. Specifically, merging URBMI and NRCMI under the URRMI policy has a positive impact on the mental health of middle-aged and elderly people and increases children's healthcare utilization. Consequently, this highlights the need to unify different types of public health insurance.

Therefore, these results highlight the importance of unifying all types of public health insurance in China. By merging different health insurance schemes, all populations can

enjoy equal benefits equivalent to those offered by UEBMI. Additionally, unifying the health insurance systems will enhance the coordination of healthcare services.

Increase Health Insurance Coverage for Children with Targeted Public Plans

In Chapter 2, we observe that 96.5% of middle-aged and elderly individuals are insured, whereas Chapter 3 reveals that only 74.7% of children are covered by health insurance. Therefore, it is important to promote health insurance coverage for children to ensure equitable access to healthcare across different age groups. To address this, policymakers could introduce more targeted health insurance policies for children. For example, including better reimbursements for regular growth check-ups and more favorable coverage for common childhood illnesses would make the plans more relevant³⁵. These targeted measures would not only improve healthcare protection but also encourage more families to enroll their children in insurance programs.

Expanding Private Health Insurance to Address Mental Health and Children's Healthcare

Our research shows that private health insurance has significant growth potential in China, particularly in areas like mental health and children's healthcare. In Chapter 3, we

³⁵ For example, the Children's Health Insurance Program (CHIP) is designed specifically for children in the United States. It covers services like routine check-ups, immunizations, dental care, and vision care. (Lave et al.,1998)

observe that both public and private health insurance can promote children's healthcare use, with private health insurance having a lower impact. While public health insurance effectively meets basic needs, it often struggles to fully support specialized services due to high demand. However, private insurance offers flexible and customized coverage, making it a better complement to public health insurance. Together, they provide more comprehensive and integrated healthcare services. This is supported by findings in Chapter 2, where people with both public and private health insurance are more likely to have good mental health than those with only public health insurance. Moreover, this collaboration improves efficiency and ensures that people receive coverage adapted to their specific needs.

Enhancing Outpatient Reimbursement Rates

After comparing different health insurance programs, we observe that the reimbursement rate and coverage for outpatient care are usually lower than those for inpatient care in China. Additionally, in Chapter 4, we find that outpatient visits have a stronger mediating effect between sleep and medical expenditure compared to inpatient visits. This indicates that outpatient services could play a more significant role in managing and controlling medical costs in this relationship. Therefore, increasing the reimbursement ratio for outpatient services is recommended. Policymakers need to pay more attention to outpatient care to ensure support is at least as much as inpatient services.

Sleep Health Promotion Plan

Chapter 4 shows the importance of sleep quality and sleep duration in controlling medical expenditure. To improve sleep quality and ensure adequate sleep duration, focusing on sleep education is necessary. This can be done through public awareness campaigns promoting healthy sleep habits and incorporating sleep assessments into regular health check-ups. Additionally, maintaining a good sleep environment is quite beneficial. For example, monitor and manage night-time noise or regulate night-time business hours. These actions will help reduce disruptions to sleep schedules. In turn, this can lower medical expenses and ease the pressure on healthcare resources.

5.3 Limitations and avenues for future research

This paper has several limitations. Firstly, the study focuses on China, and the results may not apply to other countries. Secondly, the research specifically focuses on middle-aged and elderly individuals, as well as children, which may limit the ability to generalize the findings to all age groups. Furthermore, many variables are based on self-reported information, such as health insurance details and medical expenses. This may introduce recall bias, potentially impacting the accuracy and reliability of the findings.

Future research should focus on the latest health insurance reforms. One major reform introduced in 2021 is the UEBMI family pooling policy³⁶. This policy allows UEBMI beneficiaries to share account funds with their immediate family members. This can reduce the family's financial burden of medical expenses. This policy is expected to have a significant impact, especially on family members who are not covered by UEBMI, such as children. Future studies could examine the impact of the UEBMI family pooling policy

³⁶ Details of the UEBMI family pooling policy and its implementation are available at: https://www.gov.cn/xinwen/2021-04/28/content_5603355.htm

on children's healthcare utilization or its influence on the mental health of middle-aged and elderly individuals. Additionally, further research could evaluate the cost-benefit ratio of these reforms.

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