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The Impact of Critical Illness Insurance among Older Adults in China

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by

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

Although China has made considerable progress towards universal health insurance coverage, high out-of-pocket medical expenditures due to catastrophic illnesses (e.g., cancer, heart attack, or stroke) remain a concern. To address this concern, the Critical Illness Insurance (CII) program providing additional coverage for high medical expenditures was introduced in 2012. We combine data on the timing of CII implementation across prefecture cities in China with the China Health and Retirement Longitudinal Study (CHARLS) to examine its impact on medical expenditures, inpatient utilization, health outcomes, household consumption and savings. To account for the staggered implementation across regions, we employ the Difference-in-Differences (DiD) approach proposed by Callaway and Sant'Anna (2020). We find that the CII significantly reduced out-of-pocket inpatient expenditures, but the effect on health care utilization was limited. We also find improvements in self-reported health and the number of activities of daily living limitations. In addition, the intervention of the CII program stimulates household consumption and reduces savings. Results from event-study specifications and placebo tests support the causal interpretation of our estimates. Our findings suggest that the CII program was successful in improving the financial protection and health outcomes of older adults.

The dissertation is structured as follows. Chapter one provides background on the CII program and examines the impact of the CII program on health care utilization and medical expenditures for middle-aged and older adults. Chapter two analyzes the impact of the CII

program on health outcomes. Chapter three presents the effects of the CII program on households' consumption and savings.

CHAPTER ONE:

THE IMPACT OF CRITICAL ILLNESS INSURANCE ON MEDICAL EXPENDITURES AND HEALTH CARE UTILIZATION

Introduction

Ever-increasing healthcare expenditure is a problem faced by countries worldwide, and the aging population is one of the major factors contributing to the increases (Zweifel et al., 2004). China has the highest older adult population among developing countries (*World population prospects: The 2015 revision*, 2016). China's older adult population is expected to increase significantly by 2050, with 400 million people over the age of 65 and 150 million people over the age of 80 (Zeng, 2012), which is projected to impose a new strain on public health insurance programs in the future (Zeng et al., 2019). The aging of the population corresponds to the decline of physiological functions and the health condition is in a declining stage. Therefore, the large older population will generate huge demand for health care, which will inevitably have a large impact on health services use and expenditures. The health expenditures of older adults have become a concern as the population aging process accelerates.

Health insurance can alleviate the economic pressure brought by medical treatment, enhance the fairness of healthcare services, and reduce the occurrence of catastrophic health expenditures (Cutler & Zeckhauser 1999). Therefore, it is important to understand the impact of health insurance on health expenditures for older adults and to be able to improve the accessibility and affordability of health services. Since 1998, China has progressively developed a Basic Medical Insurance System (BMI) consisting of Urban Employees Medical Insurance (UEMI), Urban Residents Medical Insurance (URMI), and the New Rural Cooperative Medical Insurance Scheme (NCMS) to provide a broad-based basic medical insurance in urban and rural areas, respectively. With the continuous improvement of the system and the increasing level of social security, universal health insurance coverage for basic medical care was virtually reached in 2013, covering around 95% of the population (*An Analysis Report of National Health Services Survey in China*, 2015). However, due to the prioritization of basic medical insurance system coverage, financial protection against major illnesses remains limited , and the current pressure on health care expenditures of urban and rural residents remains high. Previous research has shown that the out-of-pocket (OOP) payments have not been significantly reduced by these health insurance coverages, especially among rural households (Sun et al., 2009), which contributed to widening of economic inequality in China (Ma et al., 2016). Evidence suggests that NCMS and URMI only cover about half of the medical expenditures (Meng et al. 2012, Yu 2015, Li & Jiang 2017). The rigid reimbursable expenses are still beyond the affordability of residents' families, which makes them vulnerable to the vicious cycle of "sick - poor - sick again - poorer". Healthcare expenditures often pose considerable challenges to Chinese households' economic sustainability.

China has reformed its basic medical insurance for residents from a cost-control perspective, concentrating more funds on the risk of major illnesses by controlling spending on "minor" and "common" diseases. Therefore, to address these concerns and reduce the financial risk of medical expenditures, the Chinese government introduced the Critical Illness Insurance (CII) program in 2012 and it was implemented nationwide by 2016 (*Opinions of the General*

Office of the State Council on the Full Implementation of Critical Illness Insurance, 2015). CII serves as supplementary insurance to NCMS and URMI enrollees and covers medical expenditures for diseases that require expensive care. The purpose of introducing CII is to address the unbalanced and insufficient development of medical security, to address the high medical expenses associated with critical illness treatment in inpatient and outpatient settings, and with the treatment of public health diseases, to address the poverty problem associated with high medical expenses, and to compensate for the critical illness security function of basic medical insurance being deficient. Then, what impact will the emergence of the CII have on residents' medical expenses, and can it effectively alleviate residents' financial burden associated with critical illness expenses? However, there remains a gap in our understanding of this issue. Most existing literature regarding CII systems in China mainly concentrates on rural areas or reduces the incidence of catastrophic health expenditure (Li et al. 2019, Jiang et al. 2019). Few studies have quantitatively evaluated the performance of its impact on the medical expenses and health care utilization of middle-aged and older adults in urban and rural areas.

The purpose of this study is to evaluate the effect of CII on health expenditures and health service utilization among older adults in China. We empirically analyze the effect of the CII program by using the data of the China Health and Retirement Longitudinal Study (CHARLS) in 2011, 2013, 2015, and 2018. According to the purpose of this study, we formulate the inclusion criteria for the study subjects: age ⩾ 45 years old; residents enrolled in URMI, NCMS, or Urban and Rural Residents Medical Insurance (URRMI)[1]; and demographic data such as gender, education level, marital status, and household registration are controlled. Regarding the empirical methodology, we employ a doubly-robust Difference-in-Difference (DID)

[1] The URRMI system refers to some regions that have taken the lead in merging URMI with NCMS to implement a unified urban and rural residents' medical insurance system.

estimator with multiple time periods that takes advantage of the variation in the timing of the CII adoption across cities. In this setting, group-time average treatment effects are used to emphasize treatment effect heterogeneity across different dimensions and to summarize the overall treatment effect parameters.

Background on Health Insurance in China

We first briefly review the development of China's health care system to illustrate the current situation of China's health care insurance. Over the past 20 years, China has steadily reformed its health care sector with the goal of achieving universal health insurance coverage. To achieve a rational allocation of resources and ensure that everyone, including the disadvantaged, has access to government healthcare services, China began piloting a health insurance program in 1994, thus beginning healthcare reform. Health insurance reform has completed two phases: establishing an initial development of a basic health insurance plan from 1994 to 2008 and further comprehensive reform of the health insurance system from 2009 to the present. Basic medical insurance (BMI) is the countrywide government system that serves as the primary third-party payer and the backbone for healthcare financing. BMI consists of three schemes, including the Urban Employees Medical Insurance (UEMI) initiated in 1998; the New Rural Cooperative Medical Scheme (NCMS) for rural residents, which was officially established in 2003; and the Urban Resident Medical Insurance (URMI), covering mainly urban residents without formal employment in 2007 (*Decision on further strengthening rural health work* 2002, *Guiding Opinions of the State Council on Piloting Urban Residents Medical Insurance* 2007). The central and local governments directly manage the basic medical insurance system (Barber & Yao, 2010). It covers urban employees, rural residents, and unemployed urban residents. In 2008, the insurance rates in China were about 65% and 90% in urban and rural regions, respectively (Meng & Tang, 2013). By the end of 2013, insurance coverage was over 95% in both rural and urban regions (*An Analysis Report of National Health Services Survey in China,* 2013). Residents who are registered with URMI or NCMS are also eligible for Critical Illness Insurance (CII), which we describe below. In addition, some regions have taken the lead in merging URMI with NCMS to implement a unified urban and rural resident medical insurance (URRMI). These individuals would also be eligible for CII.

The New Rural Cooperative Medical Insurance Scheme (NCMS) is a voluntary insurance program for rural residents that is funded via insurance premiums paid by individuals and subsidies provided by both the local and central governments (You & Kobayashi, 2009). The rural cooperative medical fund mainly subsidizes the extensive medical expenses or hospitalization expenses of farmers who participate in NCMS (*On the Establishment of New Rural Cooperative Medical System Notice of Opinions*, 2008). Although the coverage rate had reached 92.5% by the end of 2008 (Meng & Tang, 2013), the program only provided minimal financial protection for high medical and health care expenditures among the rural poor in China (Cheng et al., 2014). In fact, Wagstaff et al. (2009) and Cheng et al. (2014) find no evidence that the NCMS reduced out-of-pocket (OOP) expenses.

The Urban Residents Medical Insurance (URMI) provides coverage for urban residents without formal employment such as older people, students, and children. It primarily covers expenses related to inpatient care and some outpatient expenses for acute diseases (Dong, 2009). Individuals or families mainly pay premiums, but the state and local financial departments provide financial assistance under specific standards (*Guiding Opinions of the State Council on Piloting Urban Residents Medical Insurance*, 2007). However, research has shown that although the program significantly increased the utilization of medical services, it did not reduce total out-of-pocket health expenses (Liu & Zhao, 2014).

Critical Illness Insurance Policy

To address concerns about the inadequate financial protection provided by NCMS, URMI and URRMI, the Critical Illness Insurance Policy was introduced as a form of supplemental insurance. In August 2012, the National Development and Reform Commission, the Ministry of Civil Affairs, the Ministry of Health, and three other departments jointly issued the "Guidance about Implementation of Critical Illness Insurance for Urban and Rural Residents", requiring the establishment of the critical illness insurance (CII) system as supplementary insurance to basic medical insurance, with the goal of further reducing individuals' financial burden caused by critical illnesses (*Guidance on the Implementation of Critical Illness Insurance for Urban and Rural Residents*, 2012). The program was initially piloted in some regions beginning in 2012 and gradually expanded to cover 25 provinces by 2014 (Wang, 2014). By the end of 2014, 700 million people, 219 prefecture-level cities[2] and 1,563 counties (cities and regions) were covered by CII, with a total of CNY 9.7 billion ($1.6 billion) set aside for the program (National Health and Family Planning Commission, 2015). The development of CII system has gone through three phases: the pilot promotion phase from August 2012 to July 2015, the full implementation phase from August 2015 to February 2020, and the standardization and improvement phase from February 2020 to the present.

CII covers all enrollees of URMI, NCMS and URRMI. In other words, NCMS, URMI or URRMI enrollees automatically become insured under the CII. This program does not require an

[2] Prefecture cities, one of China's administrative divisions, has the same administrative status as a region, autonomous prefecture, or league, and is a prefecture-level administrative region, a city with the same establishment as a region, governed by a province or autonomous region. There are a total of 293 prefecture-level cities in China.

additional premium from the insured, and its funds are allocated from the NCMS, URMI and URRMI surpluses. On this basis, the CII mainly reimburses the eligible medical expenses that still need to be borne by individuals after the basic medical insurance compensation when the insured suffers from a major illness with high medical expenses. Therefore, CII, as a secondary reimbursement based on URMI, NCMS and URRMI, focuses on inpatient medical expenses and some outpatient expenses for common major diseases of the insured residents, and it does not cover minor illnesses such as colds or bruises. In the context of this policy, critical illness is a general term for all diseases that can cause patients to suffer from economic crises. It does not refer to a specific disease but can be understood as any disease that results in high medical expenses. After applying for basic medical insurance, all patients whose OOP still exceeded the deductible, which was usually the local per capita income, were eligible for additional reimbursement, regardless of the ailment (*Guiding Opinions of the State Council on Piloting Urban Residents Medical Insurance*, 2007).

The central government proposes general guiding principles and framework for the implementation of CII, and local governments need to formulate appropriate modes in line with their socio-economic development and medical expenditure. For example, the central government requires that the total reimbursement rate should be no less than 50% (adjusted to 60% in the 2019 government work report (*Report on the Work of the Government*, 2019) when the medical bills for necessary treatment after reimbursement by NCMS and URMI exceed the annual per capita income level (*Announcement of "Guidance on the Development of Critical Illness Insurance for Urban and Rural Residents"*, 2012). Based on the central government's request, Wuhan Municipal Government also allows eligible individuals to apply for reimbursement from CII if the annual OOP amount exceeds CNY 12,000 per year (*Wuhan City* *on Further Improving the Implementation of Urban and Rural Residents' Critical Illness Insurance*, 2016). The reimbursement rate is 55% for OOP expenses between CNY 12,000 and CNY 30,000; 65% for OOP expenses between CNY 30,000 and CNY 100,000; and 75% for OOP expenses of CNY 100,000 or more. The maximum annual payment is CNY 300,000 (*Wuhan City on Further Improving the Implementation of Urban and Rural Residents' Critical Illness Insurance*, 2016). The national average reimbursement rate was 50 – 70% (*Announcement of "Guidance on the Development of Critical Illness Insurance for Urban and Rural Residents"*, 2012).

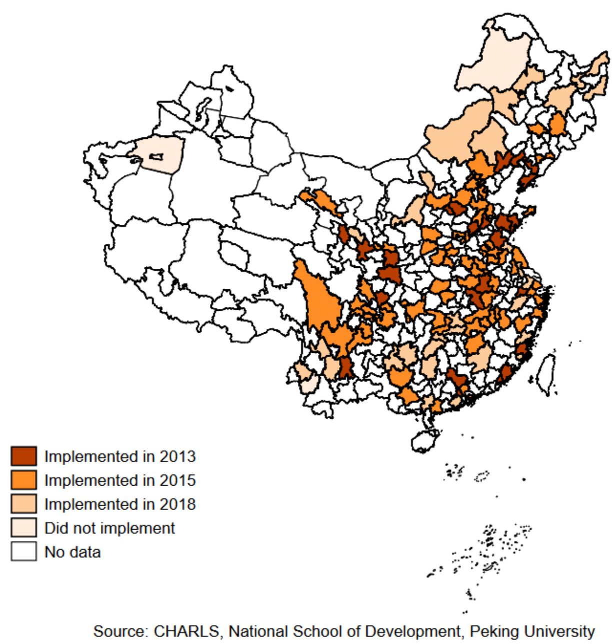

Figure 1.1. Years of CII Implementation for Sample Cities.
Source: China Health and Retirement Longitudinal Study, the Institute of Social Survey of Peking University.

We consulted the government websites and related materials of various local regions and compiled information on the time when the CII was promulgated in each prefecture city in our sample. Appendix Table A1 presents the list of prefecture cities in our sample and their date of CII implementation which are collected from each government websites and related materials of various provinces and cities. Figure 1 presents geographic and temporal variation in the implementation of CII across prefecture cities in our sample, which we use to estimate the causal impact of the CII program on health expenditures and outcomes among older adults.

Literature Review

According to an economic perspective, health insurance may increase healthcare use by reducing the marginal cost of personal care (often referred to as the out-of-pocket price of care) because of moral hazards (Pauly, 1982). On the other hand, insurance may also reduce health care utilization or expenditures, especially in the long run by improving access to necessary medical services and improving health. Additionally, persons without health insurance face high medical spending when they fall ill, limiting their options for medical services and treatment (Young & Cohen, 1991). As a result, the influence of health insurance should be investigated further.

In the United States, two landmark experiments have been conducted on the effect of health insurance. The RAND Health Insurance Experiment (HIE)[3] demonstrated that modest cost-sharing led to roughly equal amounts of decreased use of healthcare services and had no significant impact on the quality-of-care participants received (Brook et al., 2006). The Oregon Health Insurance Experiment is based on lottery drawings from a waiting list to examine the impacts of the 2008 Medicaid expansion in Oregon. It compared a control group of lottery losers to a treatment group of winners who were eligible to apply for enrollment in the Medicaid expansion program after previously being uninsured. The experiment concluded that Medicaid increased health care utilization, and reduced financial stress and depression, but had no

[3] As the largest health insurance research project in history, the HIE project began in 1971 and is supported by the Department of Health, Education, and Welfare (currently the Department of Health and Human Services).

statistically significant impact on physical health or labor market outcomes[4]. In addition to these two experiments, the general result of a large literature suggests that health insurance reduces out-of-pocket (OOP) expenditures but may not increase overall expenditures for developed countries (Kim & Kwon 2015, Paccagnella et al. 2012).

Since studies from the United States as a developed country may not be generalizable to China, this paper also focuses on some literature on the impact of health insurance in developing countries. In developing regions, the evidence is inconclusive about the effect of health insurance plans on health services utilization and medical expenses. Many empirical results indicated that health insurance systems had reduced OOP expenditures (Moradi-Lakeh & Vosoogh-Moghaddam 2015, Prinja et al. 2017), especially for the poor (Jowett et al., 2003). The Seguro Popular (SP), a health insurance system for the poor in Mexico, reduced catastrophic expenditures by 54%, as well as spending on medicines (Galárraga et al., 2009). Community-based health insurance scheme in India could protect poor households from uncertain medical expenditures (Ranson, 2002). However, literature found that Vietnam's healthcare fund for the poor has no effect on the utilization of health care services, although it might have reduced OOP health spending (Wagstaff, 2010). Disability-related inpatient expenditures were not adequately buffered by Vietnam's current public health insurance mechanisms (Palmer & Nguyen, 2012).

In recent years, several studies have researched the implementation effect of CII in China, and the results are mixed. Jiang et al. (2019) find that the CII program is associated with reduced OOP hospitalization payments in Xiantao and Yuqing counties and Li et al. (2019) find decreases in catastrophic health expenditures in Jiangsu province (Jiang et al., 2019, Li et al., 2019). In contrast, Zhong et al. (2021) find that OOP inpatient expenditures increased after the

[4] Oregon Health Insurance Experiment. NBER. (n.d.). Retrieved October 8, 2022, from https://www.nber.org/programs-projects/projects-and-centers/oregon-health-insurance-experiment

implementation of CII in Xiantao county in the 2011–2016 periods. Fang et al. (2018) examine the share of medical expenditures reimbursed by CII in four cities and conclude that it provides limited protection from catastrophic medical expenditures. Zhao (2019) uses a difference-in-differences approach to show that the CII program led to an increase in daily household consumption but not in household health expenditures.

As seen in the literature above, different studies have used different methodologies to assess the impact of various health insurance policies on health care expenditures and use. To cope with the growing trend of aging in China, medical expenditures and demand for health care services among the older adult groups are bound to rise. Thus, it is important to enhance the research on the health and health care needs of the older population in China. We collect more detailed information on the timing of implementation across prefectures in China compared to previous studies, which have examined province level variation in the timing of implementation (Zhao 2019) or have focused on a small number of cities or counties (Fang et al. 2018, Zhong et al. 2021, Li et al. 2019, Jiang et al. 2019). Previous studies on the impact of the CII, except for Zhao (2019), have estimated correlations that cannot fully rule out alternative explanations for the observed trends in health care spending. This study examined the impact of CII on healthcare expenditures and utilization for older adult groups in China through a doubly-robust DiD estimator approach. We also contribute to the literature by using this estimation approach that accounts for staggered implementation of CII across cities and heterogenous treatment effects. This approach addresses bias due to the use of already treated groups as controls in two-way fixed effect regressions. In addition, we focus on a nationally representative sample of older adults. Social insurance programs such as CII play an important role for older adults who usually have much higher health care needs than other demographics. Understanding the extent to which programs like CII improve the health and financial wellbeing of older adults will be important to address the needs of the aging population.

Research Design

Data

The data used in this study are from the 2011, 2013, 2015, and 2018 waves of the China Health and Retirement Longitudinal Study (CHARLS) conducted by the Institute of Social Science Survey of Peking University (Zhao et al., 2020). CHARLS is a biennial survey of a nationally representative sample of residents in China aged 45 and older. The baseline survey covers 28 out of 31 provinces and autonomous regions[5], 150 counties/districts, and 450 villages/urban communities across the country, involving 17,708 individuals in 10,257 households, and covers a range of social, economic, and health topics. In addition, CHARLS is one of the few micro databases that publish information at the prefectural city level, so we can match the implementation time of CII in each region with the information at the prefectural level in the database to reduce the bias in the estimation of the effect of the major medical insurance system.

Our main analysis sample includes persons aged 45 years or older, who are registered with the URMI or NCMS. We exclude those who aren't registered with the URMI or NCMS since they would not be eligible for CII. Our final sample contains 52,521 person-year observations and 13,463 individuals. Of these, 4,308 individuals reside in a prefecture city that implemented CII between the 2011 and 2013 waves (group 2013), 10,753 individuals reside in a

[5] The People's Republic of China has 31 provinces, municipalities, and autonomous regions: Anhui, Fujian, Gansu, Guangdong, Guizhou, Hainan, Hebei, Heilongjiang, Henan, Hubei, Hunan, Jiangsu, Jiangxi, Jilin, Liaoning, Qinghai, Shaanxi, Shandong, Shanxi, Sichuan, Yunnan, Zhejiang, Beijing, Tianjin, Shanghai, Chongqing, Guangxi, Inner Mongolia, Ningxia, Tibet, and Xinjiang.

prefecture city that implemented CII between the 2013 and 2015 waves (group 2015), 3,700 individuals reside in a prefecture city that implemented CII between the 2015 and 2018 waves (group 2018), and 660 individuals reside in a prefecture city that did not implement CII during our study period.

Variables

Our main dependent variables include out-of-pocket and total expenditures associated with all hospitalizations during the past year. Total inpatient expenses include the individual's out-of-pocket payments and payments by insurers. In addition, health care utilization is also used as dependent variable for inpatients. Among these variables, the variable "whether hospitalized" (no, yes) is based on respondents' responses to the question "Have you received inpatient care in the past year?" question. And the variable "number of hospitalizations" is based on the question" How many times have you received inpatient care during the past year?" All expenditure variables are adjusted for inflation using the Consumer Price Index published by the National Bureau of Statistics of China and setting 2010 as the base year (*China Statistical Yearbook*, 2013, 2015, 2018).

Our analysis accounts for various control variables that influence health care use and medical expenses. These include age, a binary indicator for male (female is the reference group), a binary indicator for being married (the reference category includes single, divorced, widowed), education (no formal education, incomplete primary education, elementary school, middle school, and high school and above), and hukou (agricultural hukou, non-agricultural hukou, and unified residence hukou). Hukou is a Chinese household registration system. It connects certain local social benefits to the hukou registration location (usually the place of birth). Notably, only those with non-agricultural hukou can register for URMI, and only those with agricultural hukou can register for NCMS. The number of family members is defined as the number of people living in this household. In addition, this study chose to include the GDP per capita and urbanization rate[6] of each prefecture city level in the corresponding year to control for prefecture characteristics that may affect individual health care utilization and health at the level of economic development. Detailed descriptions of variables are shown in Table 2 of Appendix.

Method

Since our DiD setup has more than two time periods and variation in treatment timing, we will employ an approach proposed by Callaway and Sant'Anna (2020) for average treatment effects (ATT) in staggered DiD setups with multiple groups and multiple time periods (Callaway & Sant'Anna, 2020). It exploits variation in the timing of CII implementation across prefecture cities to estimate the causal impact of the insurance program on inpatient utilization, and inpatient expenditures. The approach allows for arbitrary treatment effect heterogeneity and dynamic effects. Several recent studies have highlighted the issue of biased estimates in two-way fixed effects regression models in the presence of variation in treatment timing and heterogeneous treatment effects (Goodman-Bacon, Callaway and Sant'Anna, Abraham and Sun, deChaisemartin and deHaultfoeuille). We use the doubly-robust estimator proposed by Callaway and Sant'Anna, which addresses the concerns regarding biased estimates by comparing treated groups to untreated or not-yet-treated groups.

First, this study imposes nonparametric identification of group-time average treatment effects, $ATT\ (g,\ t)$'s, which are defined as the average treatment effect in period t for the group of units first treated in period g. Then, by aggregating the group-time average treatment effects into

[6] Urbanization rate is the ratio of the urban population to the total population.

different summary causal effect measures, various sources of treatment effect heterogeneity across groups and time periods can be highlighted. Following that, we aggregate ATT(g, t)'s into parameters that describe the overall treatment effect.

Group-time average treatment effects. First, we seek to identify the effect of the CII implementation on medical expenditures and health care utilization and focus on the disaggregated causal parameter which is the group-time average treatment effect.

The group-time average treatment effect of a group *g* at time period *t*, is denoted by

$$ATT(g,t) = E\left[Y_t(g) - Y_t(0) | G_g = 1\right].$$

G is the time period during which an individual becomes treated for the first time. G identifies the "group" of people who eventually participate in treatment. G_g is an indicator for being first treated (i.e., exposed to the CII program) in period g. In our application, we have three groups - groups that were first treated in 2013, 2015, and 2018. Note that since the CHARLS is a biennial survey and most respondents are surveyed from July to August of the survey year, we assign individuals to a treatment group if the CII program was implemented in their region before July of the survey year. Specifically, Group 2013 includes prefecture cities that implemented CII before July 2013, Group 2015 includes prefecture cities that implemented CII between August 2013 and July 2015, and Group 2018 includes prefecture cities that implemented CII between August 2015 and July 2018. For example, Haozhou city started implementing the CII program in 2014, and is assigned to Group 2015. This ensures that the utilization, expenditure, and health outcomes are measured after exposure to the CII program. The division of each city into treatment groups is shown in Table 1 of Appendix.

$Y_t(0)$ represents the untreated potential medical expenses and utilization if they had never begun receiving treatment at time period t. $Y_t(g)$ is the treated potential medical expenses and utilization experienced at time t if they were first treated at time period g. As described above, we use various measures of expenditures, utilization, and health as outcome variables. We can use the ATT (g, t) to systematically analyze changes in average treatment effects across dimensions because treatment effect heterogeneity is not limited to specific groups or time periods.

Our approach non-parametrically identifies the average treatment effect in period t for the group of units first treated in period g using the following estimator:

$$ATT_{dr}(g,t) = \mathbb{E}\left[\left(\frac{G_g}{\mathbb{E}\left[G_g\right]} - \frac{\frac{p_g(X)C}{1-p_g(X)}}{\mathbb{E}\left[\frac{p_g(X)C}{1-p_g(X)}\right]}\right)\left(Y_t - Y_{g-1} - m_{g,t}(X)\right)\right]$$

$p_g(X)$ represents the propensity score or the probability of being treated (i.e. exposed to the CII program) for the first time at time g, conditional on pre-treatment covariates X. C is an indicator for the control group, which includes "never treated" or "not-yet-treated" units but does not include "already treated" units. $m_{g,t}(X)$ represents the outcome regressions for the control group by time t. $\mathbb{E}$ denotes the expectations operator.

Identification is based on the conditional parallel trends assumption, which requires that conditional on covariates there are no other unobserved factors leading to differential trends between the treatment and control groups in the absence of treatment. In other words, we assume that conditional on covariates, the trends in medical expenditures and utilization of not-yet-treated cities would be parallel to the trends in medical expenditures and utilization of treated cities in the absence of the CII program. The doubly-robust approach of Sant'anna and Zhao (2020) combines the outcome regression approach of modeling the conditional expectation of the outcome evolution with the inverse probability weighting approach of modeling the conditional probability of being treated (Sant'Anna & Zhao, 2020). Therefore, the doubly-robust approach only requires that either one (not necessarily both) is correctly specified.

Aggregated treatment effects. Once the individual group-time average treatment effects on the treated ($ATT_{dr}(g,t)$) are estimated, we aggregate them by group, calendar time, and event time to assess treatment effect heterogeneity. First, how average treatment effects vary with length of exposure to the treatment (event-study-type estimation). Let *e* be event-time, i.e., *e* = $t - g$ denotes the duration of treatment. Thus,

$$\theta_{es}(e) = \sum_{g \in \eta} 1\{g + e \leq T\} P(G = g | G + e \leq T) ATT(g, g + e)$$

is a way to aggregate the ATT $(g,\ t)'s$ order to emphasize treatment effect heterogeneity concerning e. This is the average effect of treatment participation e time periods following treatment adoption across all groups.

Second, how average treatment effects vary across treatment groups. To gain a better understanding of the heterogeneity of treatment effects across groups, we aggregated group-time average treatment effects, taking into account the following parameters

$$\theta_{sel}(\tilde{g}) = \frac{1}{T - \tilde{g} + 1} \sum_{t=\tilde{g}}^{T} ATT\ (\tilde{g}, t)$$

where $\theta_{sel}(\tilde{g})$ is the average effects of treatment participation across all post-treatment periods for individuals in group g̃.

Third, how cumulative average treatment effects evolve over calendar time across all groups. We use an aggregated target parameter to highlight treatment effect heterogeneity when considering calendar time.

$$\theta_c(t) = \sum_{g \in \eta} 1\{t \geq g\} P(G = g | G \leq t) ATT(g, t)$$

denotes the average effect of treatment participation during time period *t* (across groups that adopted the treatment during period *t*). Consider the cumulative impact of participating in the treatment up to a specified time period as an extension to this parameter. In this paper, we want to measure how many medical expenditures or utilizations have been aspect by the CII implementation up to day $\tilde{t}$.

Aggregations into overall treatment effect parameters. Next, we summarize the group-time averaged treatment effect as the overall effect of CII implementation. The simple idea is to average all the identified group-time average treatment effects together to consider the parameter

$$\theta_W^O = \frac{1}{k} \sum_{g \in \eta} \sum_{t=2}^{T} 1\{t \geq g\} ATT(g,t) P(G = g | G \leq T)$$

Where $k = \sum_{g \in \eta} \sum_{t=2}^{T} 1\{t \geq g\} P(G = g | G \leq T)$, θ_W^O is a simple weighted average of each *ATT (g, t)* putting more weight on *ATT (g, t)*'s with larger group sizes.

Results

Descriptive analysis

Table 1.1 presents summary statistics for key variables from the 2011 wave (prior to the implementation of CII). We present summary statistics for the full analysis sample and separately for each group defined by the timing of CII implementation. Among the 13,463 observations in 2011 included in our analysis, 23.2% belong to group 2013 and are affected by CII policy, 54.1% belong to group 2015, 17.7% belong to group 2018, and 3% do not implement the policy. Overall, 90.9% of the residents have agricultural hukou. The average age of the sample is 59.13 years old. The proportion of males is relatively balanced in the sample, accounting for 47.5%. Concerning healthcare utilization, only 9.3% of the sample receives inpatient care in the past year. Furthermore, the coverage rate of URMI is relatively low, while the NCMS reaches 93%.

T-tests are used to assess the differences in variables between group 2013 and the other three groups in 2011. We do not find statistically significant differences in inpatient utilization or spending between the groups in 2011, except for the number of hospitalizations. We find a slightly larger number of hospitalizations for group 2015 relative to group 2013 and the difference is marginally significant at the 10% level. Sociodemographic characteristics do vary across groups.

Table 1.1 Characteristics of the Sample before the Implementation.

	Group 2013	Group 2015	Group 2018	Group 0	Total
Inpatient OOP expenditures	408.169	430.720	431.681	510.234	428.097
	(2628.421)	(3632.339)	(2940.539)	(2743.064)	(3265.750)
Whether hospitalized	0.093	0.095	0.089	0.094	0.093
	(0.290)	(0.294)	(0.284)	(0.292)	(0.291)
Number of hospitalizations	0.118	0.142*	0.113	0.135	0.130
	(0.427)	(0.641)	(0.423)	(0.506)	(0.554)
Total inpatient expenditures	588.051	643.477	620.999	634.884	625.932
	(3580.262)	(4717.302)	(3920.594)	(3386.249)	(4287.193)
Age	58.862	59.270**	59.254	57.865**	59.130
	(9.495)	(9.802)	(9.875)	(9.111)	(9.729)
Male	0.478	0.477	0.465	0.483	0.475
	(0.500)	(0.499)	(0.499)	(0.500)	(0.499)
No formal education	0.334	0.300***	0.309**	0.293*	0.310
	(0.472)	(0.458)	(0.462)	(0.456)	(0.462)
Incomplete primary education	0.190	0.195	0.186	0.172	0.191
	(0.392)	(0.396)	(0.389)	(0.378)	(0.393)
Elementary school	0.222	0.230	0.242*	0.300***	0.233
	(0.415)	(0.421)	(0.428)	(0.459)	(0.423)
Middle school	0.182	0.204***	0.191	0.185	0.196
	(0.386)	(0.403)	(0.393)	(0.389)	(0.397)
High school and above	0.073	0.071	0.072	0.049*	0.071
	(0.260)	(0.257)	(0.259)	(0.217)	(0.257)

Table 1.1 (Continued)

	Group 2013	Group 2015	Group 2018	Group 0	Total
Marriage	0.880	0.869	0.869	0.882	0.872
	(0.325)	(0.337)	(0.337)	(0.323)	(0.334)
Number of family members	3.497	3.699***	3.973***	3.815***	3.709
	(1.686)	(1.817)	(2.090)	(1.679)	(1.848)
Agricultural hukou	0.920	0.909*	0.904**	0.862***	0.909
	(0.271)	(0.287)	(0.295)	(0.345)	(0.287)
Nonagricultural hukou	0.071	0.088***	0.095***	0.133***	0.087
	(0.258)	(0.283)	(0.293)	(0.340)	(0.281)
Unified hukou[7]	0.008	0.003***	0.002***	0.005	0.004
	(0.091)	(0.055)	(0.039)	(0.070)	(0.063)
Rural	0.972	0.942***	0.925***	0.931***	0.946
	(0.165)	(0.233)	(0.263)	(0.254)	(0.227)
URMI	0.031	0.058***	0.085***	0.054**	0.057
	(0.173)	(0.233)	(0.279)	(0.227)	(0.231)
NCMS	0.966	0.923***	0.908***	0.926***	0.930
	(0.180)	(0.267)	(0.290)	(0.262)	(0.255)
URRMI[8]	0.006	0.023***	0.008	0.025***	0.016
	(0.078)	(0.149)	(0.091)	(0.155)	(0.126)
Capita GDP	33818.460	30032.403***	30758.873***	33561.184	31160.290
	(18229.063)	(17848.360)	(21913.272)	(13133.623)	(18751.286)
Urbanization rate	48.026	44.397***	44.601***	53.328***	45.548
	(14.968)	(13.359)	(13.037)	(17.003)	(13.957)
Number of cities	27	66	30	3	126
Number of observations	3124	7284	2649	406	13463

Source: CHARLS 2011. *Notes:* All monetary measures are deflated to 2010 CNY. T-test was used to assess the differences in variables between group 2013 and the other three groups in 2011. ***, ** and * denote statistical significance at 0.01, 0.05, and 0.10 levels, respectively.

Empirical Results for Inpatient Expenditures

We consider the cases in which one would assume that the parallel trends assumption would hold unconditionally, and when it holds only after controlling on observed characteristics X, which includes age, male, education, family size, marital status, hukou status, capita GDP, and urbanization rate.

[7] The term "unified resident hukou" refers to the reform of the hukou system in some places, which no longer distinguishes between agricultural and non-agricultural hukou, but rather unifies them into "resident hukou".
[8] URRMI: The "Urban and Rural Residents' Medical Insurance" refers to some regions that have taken the lead in merging URMI with NCMS to implement a unified urban and rural residents' medical insurance system.

Figure 1.2 presents coefficient estimates and simultaneous 95% confidence intervals from the group-time average treatment effects regression for inpatient OOP expenditures using the method suggested by Callaway and Sant'anna (2020). Panel A presents the unconditional estimates while panel B presents the results conditional on covariates. Appendix Table 3 presents the coefficient estimates and confidence intervals corresponding to Figure 1.2. All inference procedures use clustered standard errors at the prefecture city level and account for the autocorrelation of the data. Blue plots are pre-treatment estimates used to "pre-test" the parallel trend assumption, and orange plots correspond to post-treatment estimates of the treatment effect. Using the conditional parallel trends assumption means that we assume only that samples with the same characteristics would follow the same trend in OOP expenditures in the absence of treatment. None of the pre-treatment coefficient estimates are statistically significant under unconditional parallel trends assumption and conditional parallel trends assumption, and we cannot reject the joint null hypothesis that all pre-treatment effects are equal to zero. The p-value for the joint test of zero pre-treatment effects is 0.38 for the unconditional case and 0.25 for the conditional case. In other words, there is no evidence of differential trends between treated and control groups before treatment, suggesting that the parallel trends assumption is likely to hold for OOP inpatient expenditures. The findings show that group-time average treatment effects support the hypothesis that CII implementation resulted in lower inpatient OOP payments both under the unconditional parallel trends assumption and the conditional parallel trends assumption, suggesting that the results are robust.

Panel (a) of Table 1.2 under the unconditional parallel trends assumption and Panel (b) of Table 1.2 under the conditional parallel trends assumption report the treatment effect of CII on inpatient OOP expenditures aggregated in various ways, indicating that the CII implementation

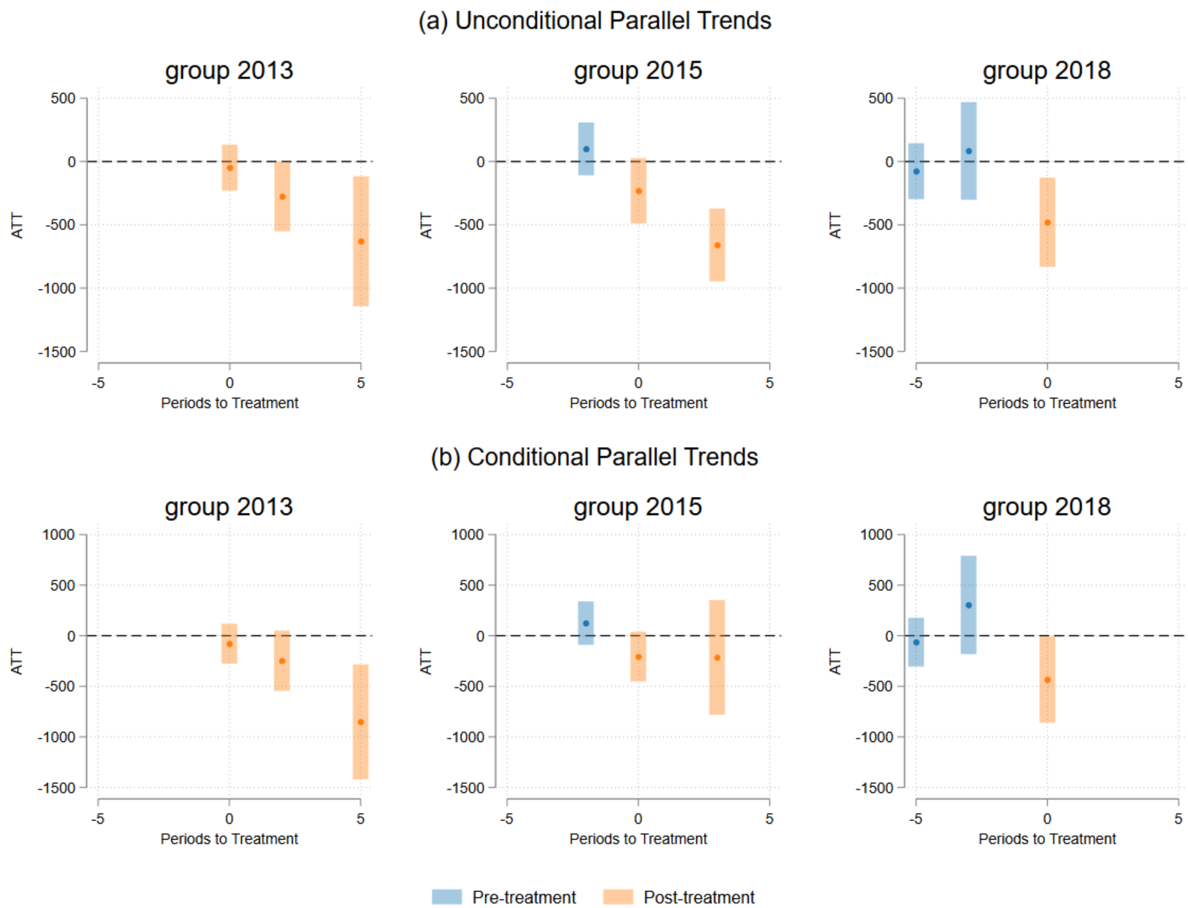

Figure 1.2. CII Group-time Average Treatment Effects on Inpatient OOP Expenditures.
Notes: The effect of the CII on inpatient OOP expenditures under the unconditional parallel trends assumption (Panel (a) and conditional parallel trends assumption (Panel (b)). Blue plots give point estimates and simultaneous 95% confidence intervals for the prefecture-level pre-treatment period clustering. These should be equal to zero under the null hypothesis of the parallel trends assumption holding in all periods. Orange plots provide point estimates and simultaneous 95% confidence intervals for the treatment effect of implementing CII clustering at the prefecture city level. The estimates use the doubly-robust estimator.

reduces inpatient OOP expenditures. The estimate for the simple weighted average treatment effect shows that the CII policy reduces OOP inpatient expenditures by CNY 391.141 for unconditional case and CNY 295.199 for conditional case for the treated group relative to the control group. Under the unconditional parallel trend, the treatment effect of CII implementation on inpatient OOP expenditures is significantly reduced in all three groups. The impact of implementing CII on the reduction in health care spending is positive and increases in magnitude the longer the city is exposed to the policy. In particular, OOP spending is estimated to decrease by CNY 228.694 from the first year of implementation of the policy in a city to CNY 629.691 in the fifth year. We also find evidence of heterogeneous treatment effects expenditures for conditional case – regions that adopted CII in 2013 and 2018 experienced larger and statistically significant decreases in OOP inpatient expenses while areas that expanded in 2015 does not experience a statistically significant decrease in OOP inpatient. The decrease in inpatient OOP expenditures after 5 years of exposure to CII is 851.3 RMB compared to a decrease of 214.1 RMB in the year of CII implementation. There are several potential explanations underlying this pattern. It is possible that more individuals become aware of the CII program over time or that the implementation of the program improves with time. While we do not have information on the quality of care received under this program or details on its implementation, we can examine whether inpatient utilization follows a similar pattern as expenditures. Another possible explanation is that the CII led to improvement in beneficiaries' health over time which may lead to lower expenditures in the long run. We explore the impact of the CII on health outcomes in the next chapter.

Table 1.2. CII Aggregated Treatment Effect Estimates on Inpatient OOP Expenditures.

	Aggregated Treatment Effects			
(a) Unconditional Parallel Trends				
Simple weighted average	-391.141^{***}			
	(88.787)			
Group-specific effects	Group 2013	Group 2015	Group 2018	
	-311.339^{***}	-431.184^{***}	-479.602^{***}	
	(115.071)	(108.083)	(179.509)	
Calendar time effects	T=2013	T=2015	T=2018	
	-47.844	-244.563^{**}	-616.288^{***}	
	(92.650)	(116.231)	(134.730)	
Event study	T+0	T+2	T+3	T+5
	-228.694^{**}	-276.151^{**}	-658.930^{***}	-629.691^{**}

Table 1.2 (Continued)

	Aggregated Treatment Effects			
	(89.906)	(140.342)	(146.589)	(261.868)
(b) Conditional Parallel Trends				
Simple weighted average	-295.199***			
	(110.211)			
Group-specific effects	Group 2013	Group 2015	Group 2018	
	-384.860***	-210.150	-434.313**	
	(128.747)	(154.907)	(217.248)	
Calendar time effects	T=2013	T=2015	T=2018	
	-78.854	-218.493*	-423.968**	
	(100.706)	(113.526)	(198.932)	
Event study	T+0	T+2	T+3	T+5
	-214.112**	-247.221	-214.415	-851.304***
	(95.412)	(152.033)	(289.498)	(289.558)

Data source: 2011-2018 waves of CHARLS. *Notes:* The table reports the aggregate treatment effect parameters for inpatient OOP expenditures under unconditional parallel trends in Panel (a) and conditional parallel trends in Panel (b), along with prefecture city level clustering. The "Simple Weighted Average" row reports the weighted mean of the group-time averaged treatment effects (by group size) for all available groups. The "Group-Specific Effects" row summarizes the average treatment effects by the time of CII implementation; here, g indicates the year in which a city was first treated. The "Event Study" row reports the average treatment effect of exposure to CII implementation; here, e indicates the time of exposure to treatment. The "Calendar Time Effect" row reports the average treatment effect by year; t indicates the annual index. The estimates use the doubly robust estimator. ***, ** and * denote statistical significance at 0.01, 0.05, and 0.1 levels, respectively. Sample size: 52,521 observations. Covariates: age, male, education level, marriage, family size, agricultural hukou, nonagricultural hukou, unified hukou, per capita GDP and urbanization rate. Group 2013 refers to cities that began implementing the policy before July 2013. Group 2015 refers to cities that began implementing the policy from August 2013 to July 2015. Group 2018 refers to cities that began implementing the policy from August 2015 to July 2018.

Figure 1.3 presents coefficient estimates and simultaneous 95% confidence intervals from the group-time average treatment effects for total inpatient expenditures. Appendix Table 4 presents the coefficient estimates and confidence intervals corresponding to Figure 1.3. None of the pre-treatment coefficient estimates are statistically significant both under unconditional parallel trends assumption and conditional parallel trends assumption. The p-value for the joint test of all pre-policy treatment effects under unconditional parallel trends assumption is 0.60 and under conditional parallel trends assumption is 0.28, which suggests that the parallel trends assumption is satisfied. In addition, from the graph, we find that the treatment effect of implementing CII in each group is not significant.

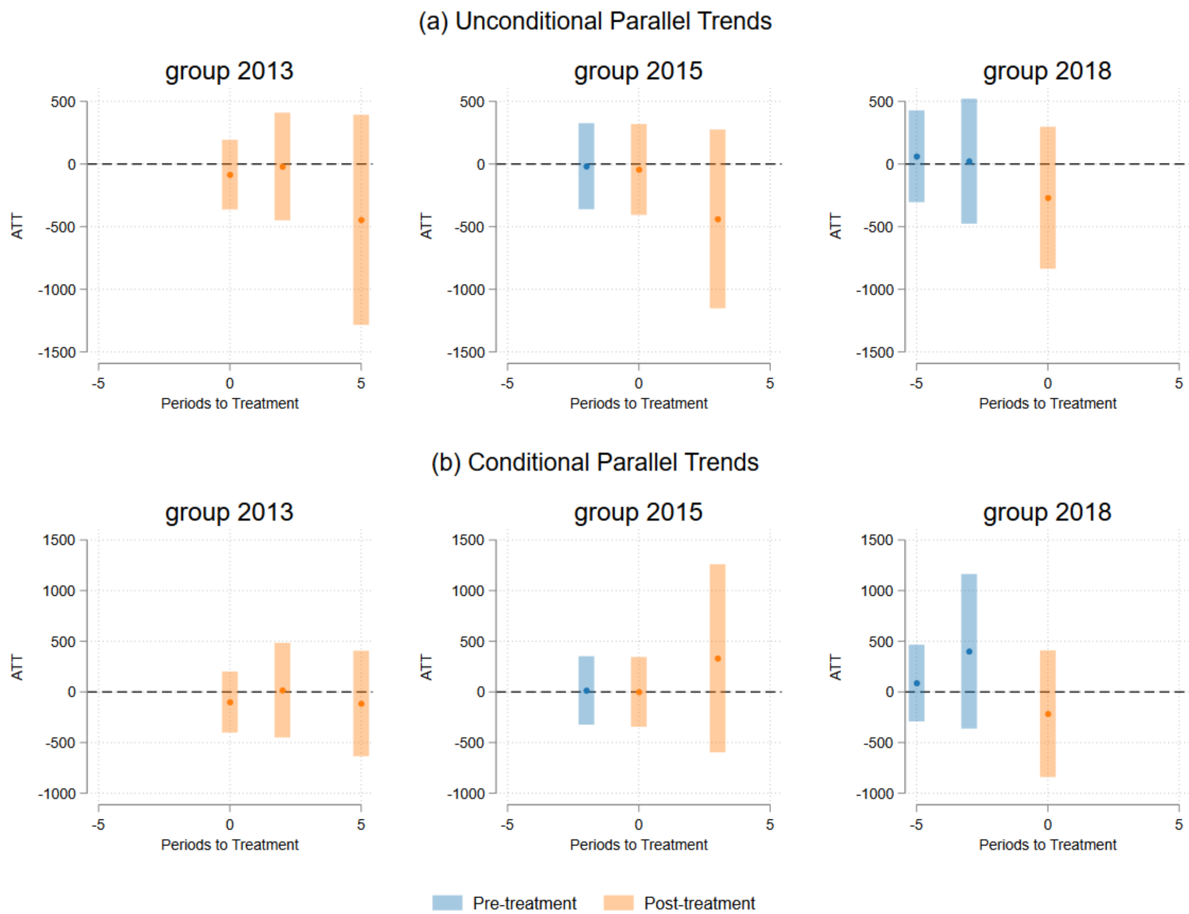

Figure 1.3. CII Group-time Average Treatment Effects on Total Inpatient Expenditures.
Notes: The effect of the CII on total inpatient expenditures under the unconditional parallel trends assumption (Panel (a) and conditional parallel trends assumption (Panel (b)). Blue plots give point estimates and simultaneous 95% confidence intervals for the prefecture-level pre-treatment period clustering. These should be equal to zero under the null hypothesis of the parallel trends assumption holding in all periods. Orange plots provide point estimates and simultaneous 95% confidence intervals for the treatment effect of implementing CII clustering at the prefecture city level. The estimates use the doubly-robust estimator.

Table 1.3 shows aggregated treatment effects of CII on total inpatient spending. Interestingly, we find that total inpatient expenditures are not significantly affected in response to the CII policy. The pre vs post change in total inpatient expenditures for the treated groups is CNY 213.794 for unconditional case and CNY 39.377 for conditional case higher than the pre vs post change for the control group, and neither result is significant. Under the conditional parallel trends assumption, we also find that total inpatient expenditures decrease in the regions that adopted CII in 2013 and 2018 and increase in the regions that adopted CII in 2015, but neither is significant. The reduction in total expenditures may be due to changes in utilization or price changes. While we do not have information on prices, we can evaluate changes in inpatient utilization (shown below).

Table 1.3. CII Aggregated Treatment Effect Estimates on Total Inpatient Expenditures.

	Aggregated Treatment Effects			
(a) Unconditional Parallel Trends				
Simple weighted average	-213.794			
	(179.045)			
Group-specific effects	Group 2013	Group 2015	Group 2018	
	-180.258	-227.594	-269.084	
	(187.326)	(214.404)	(289.176)	
Calendar time effects	T=2013	T=2015	T=2018	
	-84.519	-36.340	-407.077	
	(141.952)	(158.322)	(325.397)	
Event study	T+0	T+2	T+3	T+5
	-94.068	-19.674	-438.274	-445.624
	(129.459)	(219.237)	(364.298)	(427.882)
(b) Conditional Parallel Trends				
Simple weighted average	39.377			
	(153.162)			
Group-specific effects	Group 2013	Group 2015	Group 2018	
	-66.076	154.583	-215.293	
	(160.043)	(247.822)	(318.840)	
Calendar time effects	T=2013	T=2015	T=2018	
	-99.774	5.511	108.747	
	(153.619)	(154.761)	(269.752)	
Event study	T+0	T+2	T+3	T+5
	-63.313	17.471	331.910	-113.969
	(138.498)	(238.211)	(473.719)	(265.653)

Data source: 2011-2018 waves of CHARLS. *Notes:* The table reports the aggregate treatment effect parameters for total inpatient expenditures under unconditional parallel trends in Panel (a) and conditional parallel trends in Panel (b), along with prefecture city level clustering. The "Simple Weighted Average" row reports the weighted mean of the group-time averaged treatment effects (by group size) for all available groups. The "Group-Specific Effects" row summarizes the average treatment effects by the time of CII implementation; here, g indicates the year in which a city was first treated. The "Event Study" row reports the average treatment effect of exposure to CII implementation; here, e indicates the time of exposure to treatment. The "Calendar Time Effect" row reports the average treatment effect by year; t indicates the annual index. The estimates use the doubly robust estimator. ***, ** and * denote statistical significance at 0.01, 0.05, and 0.1 levels, respectively. Sample size: 52,521 observations. Covariates: age, male, education level, marriage, family size, agricultural hukou, nonagricultural hukou, unified hukou, per capita

GDP and urbanization rate. Group 2013 refers to cities that began implementing the policy before July 2013. Group 2015 refers to cities that began implementing the policy from August 2013 to July 2015. Group 2018 refers to cities that began implementing the policy from August 2015 to July 2018.

Empirical Results for Health Care Utilization

Next, we examine the impact of the CII program on a binary indicator for receiving any care in the past year and on the number of inpatient visits during the past year (Table 1.4 and Figure 1.4). Appendix Table 5 presents the coefficient estimates and confidence intervals corresponding to Figure 1.4. Panel (a) reports the results of "whether hospitalized" and panel (b) reports the effects of "number of hospitalizations". From the event study graph, we find no evidence of pre-existing trends in both "whether hospitalized" and "number of hospitalizations". The p-value for the joint test of all pre-policy treatment effects is 0.77 for whether hospitalized and 0.50 for the number of hospitalizations, which suggests that the parallel trends assumption is satisfied. Focusing on the conditional treatment effects, we do not find significant changes in either the extensive or intensive margin of inpatient care. The unconditional effect of the CII on the likelihood of hospitalization is significant and negative but this effect becomes insignificant when we account for covariates. We find a 6.7 percentage point decrease in the probability of being hospitalized (significant at the 10% level) and a 0.093 decrease in the number of hospitalizations, five years after CII implementation. There is some evidence of increased inpatient utilization 3 years after CII implementation, however, the estimates are noisy. Overall, these results suggest that the CII reduced OOP payments but did not change inpatient utilization or total spending.

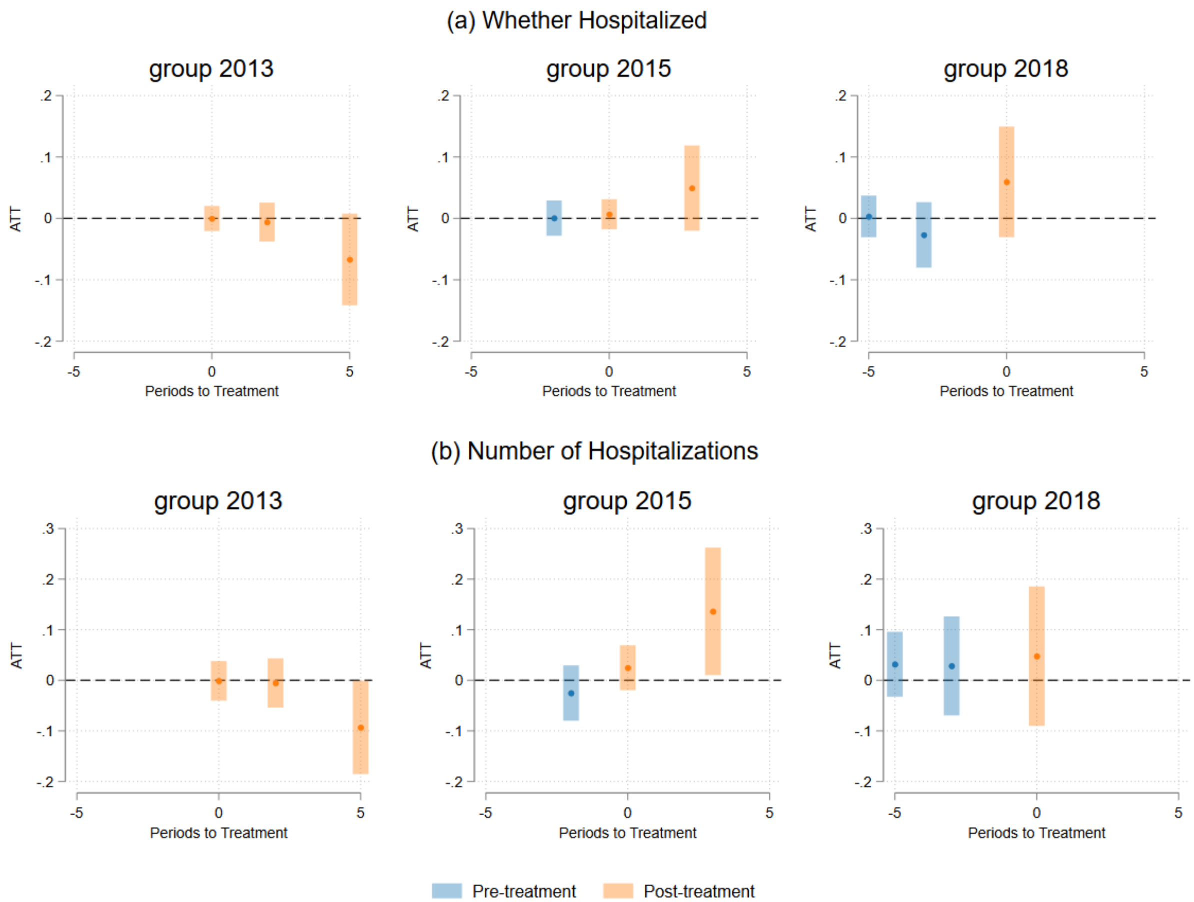

Figure 1.4. CII Group-time Average Treatment Effects on Health Care Utilization.
Notes: The effect of the CII on whether hospitalized is Panel (a) and the number of hospitalizations is Panel (b). Blue plots give point estimates and simultaneous 95% confidence intervals for the prefecture city level pre-treatment period clustering. These should be equal to zero under the null hypothesis of the parallel trends assumption holding in all periods. Orange plots provide point estimates and simultaneous 95% confidence intervals for the treatment effect of implementing CII clustering at the prefecture city level. The estimates use the doubly-robust estimator.

Table 1.4. CII Aggregated Treatment Effect Estimates on Health Care Utilization.

	Aggregated Treatment Effects		
(a) Whether Hospitalized			
Simple weighted average	0.011		
	(0.013)		
Group-specific effects	Group 2013	Group 2015	Group 2018
	-0.024	0.026	0.059
	(0.016)	(0.019)	(0.046)
Calendar time effects	T=2013	T=2015	T=2018
	-0.000	0.003	0.021
	(0.010)	(0.011)	(0.023)

Table 1.4 (Continued)

	Aggregated Treatment Effects			
Event study	T+0	T+2	T+3	T+5
	0.014	-0.006	0.049	-0.067*
	(0.013)	(0.016)	(0.035)	(0.038)
(b) Number of Hospitalizations				
Simple weighted average	0.034			
	(0.024)			
Group-specific effects	Group 2013	Group 2015	Group 2018	
	-0.032	0.076**	0.048	
	(0.023)	(0.034)	(0.070)	
Calendar time effects	T=2013	T=2015	T=2018	
	-0.001	0.016	0.059	
	(0.020)	(0.018)	(0.045)	
Event study	T+0	T+2	T+3	T+5
	0.022	-0.005	0.136**	-0.093**
	(0.020)	(0.025)	(0.064)	(0.047)

Data source: 2011-2018 waves of CHARLS. *Notes:* The table reports the aggregate treatment effect parameters for whether hospitalized in Panel (a) and the number of hospitalizations in Panel (b), along with prefecture city level clustering. The "Simple Weighted Average" row reports the weighted mean of the group-time averaged treatment effects (by group size) for all available groups. The "Group-Specific Effects" row summarizes the average treatment effects by the time of CII implementation; here, g indicates the year in which a city was first treated. The "Event Study" row reports the average treatment effect of exposure to CII implementation; here, e indicates the time of exposure to treatment. The "Calendar Time Effect" row reports the average treatment effect by year; t indicates the annual index. The estimates use the doubly robust estimator. ***, ** and * denote statistical significance at 0.01, 0.05, and 0.1 levels, respectively. Sample size: 52,521 observations. Covariates: age, male, education level, marriage, family size, agricultural hukou, nonagricultural hukou, unified hukou, per capita GDP and urbanization rate. Group 2013 refers to cities that began implementing the policy before July 2013. Group 2015 refers to cities that began implementing the policy from August 2013 to July 2015. Group 2018 refers to cities that began implementing the policy from August 2015 to July 2018.

Heterogeneity Analysis

Based on the above empirical results, we find that the CII policy significantly decreases OOP expenditures but has no significant impact on health care use. Although the CII can contribute to a reduction in the burden of medical spending, the stimulus effect that the CII can have may vary depending on the financial ability, age group, and location of the family. To further explore the heterogeneity of the impact of CII on health care utilization and medical expenditures of middle-aged and older adults, we first divide the sample into urban and rural samples according to household registration and the type of basic health insurance enrolled, and then performed DID with multiple time periods regression analysis, and the simple weighted average treatment effects are presented in the first and second columns of Table 1.5. The results show that the implementation of CII significantly reduces inpatient OOP spending for both rural and urban residents. Among them, the OOP spending is significantly reduced by CNY 276.101 for rural residents and CNY 1768.294 for urban residents. The implementation of the policy increases the number of hospitalizations of rural residents but has no significant effect on urban residents. There are positive effects of CII implementation on whether urban and rural residents are hospitalized, but none of the effects are statistically significant.

Then, we categorize the middle-aged and older groups in the sample according to China's classification standards, i.e., the group under 60 years of age in the sample is the middle-aged group and those over 60 years of age are the older groups. The results are reported in the third and fourth columns of Table 1.5. The results show that CII implementation significantly reduces OOP expenditures by CNY 355.796 for middle-aged adults and has no significant effect on older adults. There is also a significant increase in the number of hospitalizations among the older adults group, which may be due to their poorer physiology, greater susceptibility to illness, and recurring conditions.

In addition, the annual per capita household income of the sample was sorted by quartiles, and the sample was divided into low-income, middle-income, and high-income groups. The results are reported in the last three columns of Table 1.5. The policy implementation decreases inpatient OOP spending by CNY 268.734 for the middle-income group and CNY 1371.922 for the high-income group but has no significant impact on the low-income group. For low-income residents, the starting threshold for CII is high, usually at the local per capita disposable income of the previous year. The low-income group's income does not even reach this threshold, so the positive effect of the system's implementation is limited.

Table 1.5. Results of Heterogeneity Analysis on Health Care Use and Medical Expenditures.

Variables	Rural	Urban	Middle-aged	Older	Low-income	Middle-income	High-income
Inpatient OOP expenditures	-276.101**	-1768.294***	-355.796***	-300.215	-74.130	-268.734**	-1371.922*
	(112.699)	(680.050)	(110.857)	(316.132)	(416.862)	(135.531)	(822.073)
Total inpatient expenditures	63.614	-1016.779	-272.343	575.068	809.116	-89.186	-411.353
	(155.736)	(889.110)	(177.510)	(368.200)	(548.170)	(223.713)	(547.092)
Whether hospitalized	0.021	0.025	0.003	0.014	0.007	0.019	-0.025
	(0.015)	(0.041)	(0.019)	(0.012)	(0.042)	(0.023)	(0.036)
Number of hospitalizations	0.059**	-0.006	-0.012	0.072**	0.038	-0.026	-0.008
	(0.029)	(0.096)	(0.038)	(0.028)	(0.078)	(0.032)	(0.049)
N	49345	3176	25053	27468	17236	17223	17223

Data source: 2011-2018 waves of CHARLS. *Notes:* The table reports the simple weighted average treatment effects of heterogeneity analysis for health care use and medical expenditures. The estimates use the doubly robust estimator. ***, ** and * denote statistical significance at 0.01, 0.05, and 0.1 levels, respectively. Covariates: age, male, education level, marriage, family size, agricultural hukou, nonagricultural hukou, unified hukou, per capita GDP and urbanization rate.

Robustness Check

To test the reliability of the results on the impact of CII policy on health care costs, the following robustness check is conducted in this study, and the regression results are shown in Table 1.6. For the robustness check, three possible problems in the empirical study are considered. First, there may be a portion of urban and rural residents who participate in other medical insurance such as public health care, employee health insurance, or commercial health insurance, which affects their financial affordability and consumption behavior, thus affecting the reliability of the empirical results. Therefore, we eliminate those samples that participated in government medical insurance, medical aid, urban employee medical insurance, or commercial medical insurance by further identifying and locking the medical insurance participation information of all samples, and then conducting regression analysis. The results, shown in the first column of Table 1.6, indicate that OOP expenditures decrease by CNY 284.31 after the CII implementation, while the other three dependent variables are not significant.

Second, the Urban and Rural Residents' Medical Insurance system (URRMI) may have similar effects to the CII policy, and thus may affect the outcome of the effect of the CII policy. In 2016, China's State Council issued the Opinions on Integrating the Urban and Rural Residents Basic Medical Insurance System, which required the integration of NCMS and URMI and the establishment of a unified urban and rural residents' medical insurance system to unify the medical insurance catalog, coverage, and treatment, etc. (*Opinions on Integrating the Urban and Rural Residents Basic Medical Insurance System,* 2016). However, the reform of the integrated urban and rural residents' basic medical insurance system is similar to the reform of the CII policy, and they are both "from something to something better" improvements. To accurately identify the effects of CII, we exclude the sample with registered URRMI to ensure the robustness of the study design. The results in the second column of Table 1.6 show that there is a significant decrease in OOP expenditures and a significant increase in whether hospitalized and how many hospitalizations after the implementation of CII.

Furthermore, the sample used in the main regression results matched the interview year with the policy implementation time of each prefecture-level city, but it does not exactly match the interview month in the sample, which affects the accuracy of the regression results. Therefore, in this section, we match the interview year and month of the sample to the implementation time of each prefecture-level city, and then re-estimate the impact of CII on healthcare utilization and healthcare expenditure. The third column of Table 1.6 presents the simple average treatment effects for the sample grouped using interview dates. The pre vs post change in OOP inpatient expenditures for the treated groups is CNY 304.2 lower than the pre vs post change for the control group. In addition, following the implementation of CII, we observe there is no significant effect on total inpatient expenditures, whether hospitalized and the number of hospitalizations. Overall, the three robustness tests indicate that the implementation of the CII policy is effective in reducing residents' inpatient OOP expenditures.

Table 1.6. Robustness Check on Health Care Use and Medical Expenditures.

Variables	Without other health insurance	Without URRMI	Grouping using interview dates[9]
Inpatient OOP expenditures	-284.310**	-246.804**	-304.200***
	(117.002)	(110.788)	(111.708)
Total inpatient expenditures	77.626	228.441	29.333
	(152.638)	(187.943)	(152.502)
Whether hospitalized	0.014	0.026**	0.010
	(0.013)	(0.011)	(0.013)
Number of hospitalizations	0.038	0.071***	0.033
	(0.024)	(0.026)	(0.024)
N	50011	49328	52521

Data source: 2011-2018 waves of CHARLS. *Notes:* The table reports the simple weighted average treatment effects of robustness check for health care use and medical expenditures. The estimates use the doubly robust estimator. ***, ** and * denote statistical significance at 0.01, 0.05, and 0.1 levels, respectively. Covariates: age, male, education level, marriage, family size, agricultural hukou, nonagricultural hukou, unified hukou, per capita GDP and urbanization rate.

Placebo Test

To rule out the possibility that these decreases in spending are driven by unobserved policies or shocks, we perform a placebo test. Specifically, we estimate the same regressions for the sample of persons who are not enrolled in NCMS, URMI, and URRMI with a total of 11,233 observations. These individuals are not eligible for CII and therefore we should find no effect if our estimates represent the causal effect of CII. However, these persons would be exposed to the same unobserved policies or economic shocks as our main analysis. Therefore, if our main

[9] "Grouping using interview dates" is a grouping obtained using the year and month in which the respondents were interviewed matched to the time of CII implementation.

estimates are confounded by the effects of unobserved policies or shocks, we should also find a decrease in inpatient utilization and spending for persons who are not enrolled in NCMS, URMI, and URRMI. Coefficient estimates and simultaneous 95% confidence intervals from the group-time average treatment effects regression are shown in Figure 1.5. Appendix Table 6 presents the coefficient estimates and confidence intervals corresponding to this graph. The simple average treatment effects results from the placebo test are presented in Table 1.7. The simple average treatment effect on the treated for OOP inpatient spending is positive (the opposite sign of our main effect) and it is not statistically significant. Similarly, for total inpatient spending and inpatient utilization, we find statistically insignificant effects. Together with the event study graphs, the placebo estimates suggest that our main estimates are not driven by unobserved policies or shocks.

In summary, we find no evidence of a significant decrease in utilization or spending for the placebo sample, suggesting that our main estimates are not driven by unobserved policies or shocks. The CII did not significantly impact medical expenses and utilization for the sample with neither NCMS, URMI nor URRMI, which is consistent with our expectations because the CII only covers residents with either NCMS, URMI or URRMI.

Discussion

After the implementation of CII, inpatient OOP payments significantly decreased for a sample of middle-aged and older persons. A published systematic evaluation of evidence on the effectiveness of interventions has demonstrated that implementation within existing health insurance plans involving reducing or eliminating co-payments for disease-specific treatments can significantly reduce out-of-pocket expenditures (Essue et al., 2014). The CII improves equity

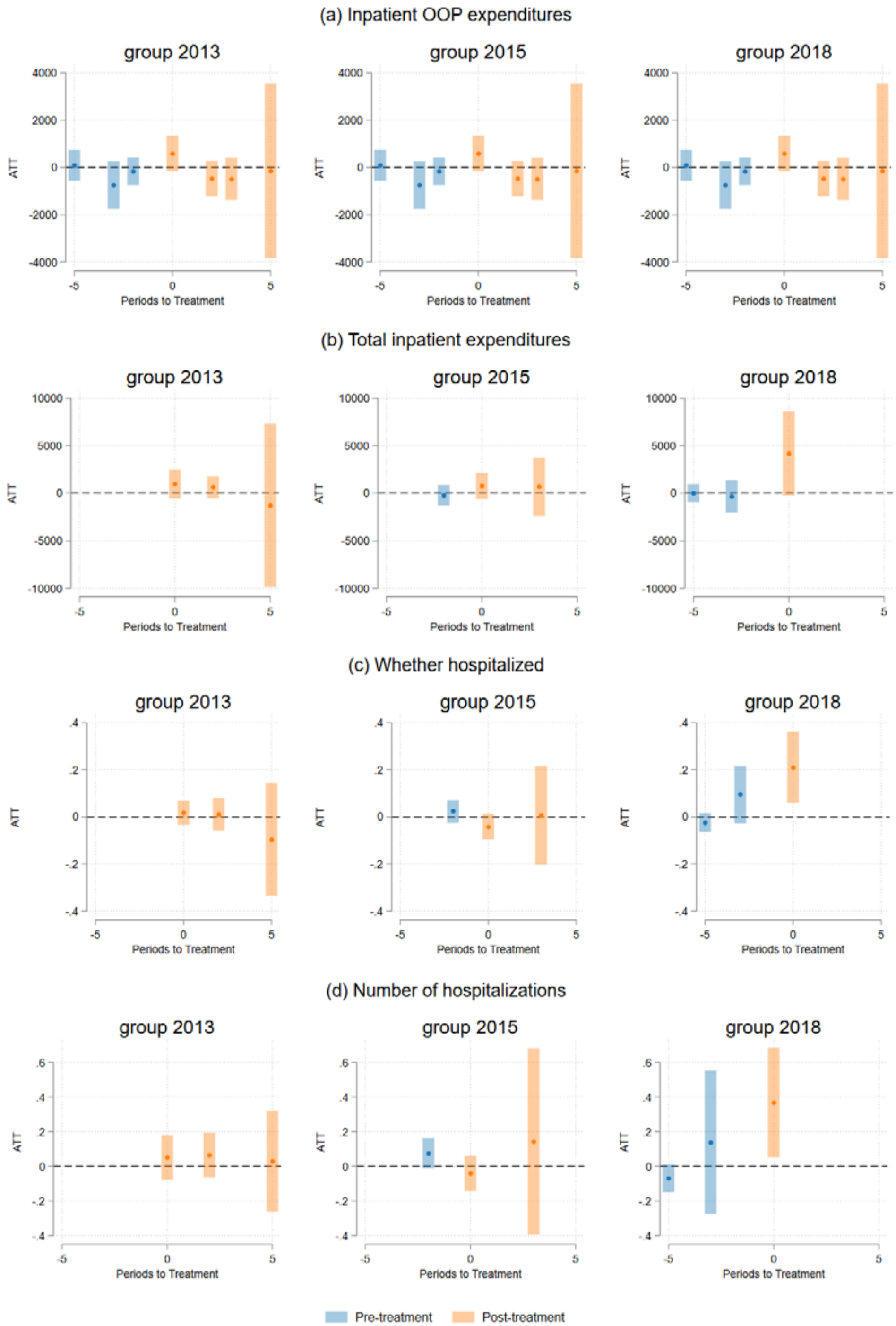

Figure 1.5. CII Group-time Average Treatment Effects on Health Care Use and Medical Expenditures of Placebo Test.

Notes: The effect of the CII on inpatient OOP expenditures is Panel (a), total inpatient expenditures is Panel (b), whether hospitalized is Panel (c), and number of hospitalizations is Panel (d). Blue plots give point estimates and simultaneous 95% confidence intervals for the prefecture city level pre-treatment period clustering. These should be equal to zero under the null hypothesis of the parallel trends assumption holding in all periods. Orange plots provide point estimates and simultaneous 95% confidence intervals for the treatment effect of implementing CII clustering at the prefecture city level. The estimates use the doubly-robust estimator.

Table 1.7. Placebo Test on Health Care Use and Medical Expenditures.

Variables	Simple weighted average	Pre-trend p-value
Inpatient OOP expenditures	113.258 (331.630)	0.636
Total inpatient expenditures	875.984 (606.095)	0.894
Whether hospitalized	0.004 (0.020)	0.272
Number of hospitalizations	0.084 (0.053)	0.329
N	11233	

Data source: 2011-2018 waves of CHARLS. *Notes:* The table reports the simple weighted average treatment effects and p-value of pre-trend of placebo test for health care use and medical expenditures. The estimates use the doubly robust estimator. ***, ** and * denote statistical significance at 0.01, 0.05, and 0.1 levels, respectively. Covariates: age, male, education level, marriage, family size, agricultural hukou, nonagricultural hukou, unified hukou, per capita GDP and urbanization rate.

between the rich and the poor through secondary reimbursement of high medical expenditures, thereby reducing patients' out-of-pocket expenses and alleviating financial burdens. From the influence of each group, the decrease in inpatient expenses and OOP increases with exposure to the policy. The longer CII is in place, the larger the reductions in OOP medical payments. Many patients are not aware of the content of the policy during the first year of CII implementation. With the introduction of CII, more and more patients benefited from it. The longer the duration of the intervention, the more effective the intervention was. In addition, in the heterogeneity analysis, we find that the CII adoption has a limited effect on the older age groups older than 60 and the low-income groups, which are the groups facing higher health risks and the greatest financial burden. This may be since such vulnerable groups have lower economic affordability, are less willing to receive treatment when they become ill and have less opportunity to take advantage of the CII, and thus are less likely to benefit from the policy. Most regions currently use the average annual income of urban and rural residents in the previous year as the criterion for judging the threshold, but the annual income of the net-consuming older adults and disadvantaged low-income groups cannot even reach that criterion, so the positive effect of system implementation on them is limited.

In addition, there is an increase but insignificant in the effect of CII on whether residents are hospitalized and the number of hospitalizations. We also find some heterogeneity - whether residents are hospitalized and the number of hospitalizations decreased in areas where CII was implemented in 2013, and the number of hospitalizations among urban residents, middle-aged groups, and middle-and high-income groups decreased, but these impacts are not statistically significant. Since the deduction amount of the CII is based on the per capita disposable income of residents, many low-income families cannot even pay this threshold. For example, the deductible line of Guangxi Autonomous Region in 2015 requires all districts and cities to make their own decisions, which should not be higher than CNY 15,000 (*Notice on the implementation plan of urban and rural residents' critical illness insurance work of Guangxi*, 2015). Chongqing's deductible standard in 2016 is CNY 12,917 (*Notice on matters related to critical illness insurance for urban and rural residents* 2016). For poor patients, the deductible expense is too high. Mainly when the CII only covers the part above the threshold, families still have to bear the rest of the medical expenses themselves. Therefore, they will not benefit from implementing the CII policy and thus will not seek medical care.

Therefore, we suggest that, in terms of system design, the level of protection of the major medical insurance system should be further increased in the future and a differentiated threshold should be designed. For disadvantaged groups such as the older and low-income people, the funding standard should be lowered to reduce the pressure on their contributions. In addition, the design of the system compensation should also be tilted, such as lowering the threshold and increasing the reimbursement ratio and cap line.

However, this study has several limitations. We assess the impact of CII before and after the intervention using pooled panel data, but various biases may arise during implementation. China is implementing health system reforms, while chronically high health care spending and a crowded health care environment have resulted in fewer and fewer people willing to receive health care services. Thus, there may be other factors interfering with this policy simultaneously, and these confounding factors may lead us to biased estimates of the role of CII. Second, due to the limitations of the CHARLS database questionnaire setup and the difficulty of collecting relevant fragmented data, we could not obtain total OOP medical expenditures for the current year sample, which should have included both outpatient OOP expenditures and inpatient OOP expenditures. Therefore, some of the samples that may incur frequent low to moderate medical expenditures are not well taken into account, and some of the targets that should be examined but exist are lost and thus may impact our findings.

Conclusion

The varying process of implementation of the CII in different regions allows this study to analyze the impact of the implementation of CII on health care utilization and healthcare expenditures of middle-aged and older adults using multiple time periods DID method with doubly-robust estimator. In this chapter, we evaluate the effectiveness of the CII system in China in terms of healthcare spending and health utilization before and after implementing the CII system. These results suggest that the CII reduced OOP inpatient expenditures but did not have a significant effect on inpatient service utilization. The overall regression results are also in line with our expectations because CII is based on the existing urban and rural basic medical insurance to compensate further residents who have incurred extensive medical expenditures, thereby reducing the economic burden of residents. The reliability of these findings is further verified by robustness check and placebo tests. In addition, heterogeneity analysis find that CII implementation has a significant reduction in out-of-pocket payments mainly for middle-aged people under 60 years of age and middle- and high-income groups.

CHAPTER TWO:

THE IMPACT OF CRITICAL ILLNESS INSURANCE ON HEALTH OUTCOMES

Introduction

As one of China's most crucial health care reform programs in recent years, critical illness insurance (CII) is designed to reduce OOP, improve health outcomes, and reduce illness-induced impoverishment. However, the current studied literature still lacks credible evidence on CII that its implementation improves health status and reduces out-of-pocket medical expenditures. In the previous chapter, we find that the implementation of CII has a limited effect on inpatient utilization. To assess whether this limited utilization represents reduced access to services or a reduction in medically unnecessary care, we examine the impact on health. The purpose of this paper is to contribute to the literature by examining the impact of China's current supplemental health insurance system, known as CII, on health outcomes. We focus specifically on China's middle-aged and older adult population, the group most vulnerable to ill health and disease.

China has entered an aging society and will continue to age rapidly in the future, while many older adults are still relatively poor. Average life expectancy is also gradually increasing in China. The best population forecast predicts that as China reach a life expectancy of about 80 years, the life expectancy of Chinese people will increase, which is twice that of 100 years ago (Chinese Academy of Social, 2010). The challenge of the aging population in China will come from two aspects - economic support and aged care. Healthy aging can potentially reduce the burden on these two fields by reducing or delaying the demand for financial support and older people care (Smith et al., 2014). Therefore, it is a challenge for China to realize healthy aging and reduce the social and economic burden.

Older adults may experience an increased incidence of chronic diseases, increased risk of depression, increased prevalence of dementia, and decreased functionality. For example, chronic diseases, including hypertension, cardiovascular diseases, cancer, diabetes, and chronic respiratory diseases, have become a significant health threat to the older population and their families and a significant public health problem affecting the country's economic and social development. The proportion of deaths from chronic diseases among the population is as high as 86.6% of the total number of deaths, causing a disease burden that already accounts for more than 70% of the total disease burden (*Interpretation of China's Medium-and Long-term Plan for the Prevention and Treatment of Chronic Diseases*, 2017). Furthermore, due to the gradual decline of physical and mental functions, the disability of activities of daily living (ADL) is prevalent among older adults. ADL limitations impose burdens on the older adults and their family due to caregiving challenges, limitations on labor force participation, and financial strain, and poses challenges to public health. These diseases have brought substantial economic burdens to patients, caregivers, and public projects such as medical insurance and Medicaid.

As an important component of public health care and social security in China, the health insurance system is designed to promote people's health, improve accessibility, and increase the equity of health care services. There is evidence that people without health insurance receive less critical care services and have worse health outcomes (Fowler et al., 2010). Health insurance may affect health outcomes by increasing access to necessary health care in a timely fashion. Health insurance programs may also improve mental health by reducing financial strain

(Ayyagari & Shane, 2015). The purpose of CII implementation is to improve the residents' health and enhance the accessibility of healthcare services by reducing the price of healthcare services. Our previous research found that CII reduced inpatient OOP expenses but did not have a sufficient impact on improving health care utilization. CII has been implemented for nine years, but there is limited empirical research on improving the population's health status, which is a central goal of China's healthcare reform.

This chapter examines the relationship between the CII and the health of older adults, using panel data from the China Health and Retirement Longitudinal Study (CHARLS). We investigated whether this introduction of health insurance would have a causal effect on health functioning, as well as reveal any heterogeneity in this relationship. To observe the influence of CII on measurable outcomes of different dimensions of the insured, that is, the group-time average treatment effects, we adopted the doubly-robust Difference-in-Differences (DiD) estimator with multiple time periods proposed by Callaway and Sant'Anna in 2020.

Literature Review

Although some studies have found that people with health insurance are healthier than those without (Franks et al. 1993, McWilliams et al. 2004, Fowler et al. 2010), the causal relationship between health insurance and health outcomes is not well understood. Because health insurance coverage is correlated with many other factors that determine health status, the difference between the insured and uninsured individuals may not represent the causal effect of health insurance. Insurance coverage may also be influenced by health status (Levy & Meltzer, 2008).

Some literature has recently used public health insurance expansion as a natural experiment to explore the causal relationship between health insurance and multiple outcomes, with mixed results. For example, people with Medicare eligibility at age 65 in the US have more health care utilization and a slight improvement in self-reported health status but no reduction in mortality (Card et al., 2004). By assessing changes in self-reported health trajectories at age 65, obtaining Medicare increases the likelihood that survey participants reported being excellent or very healthy (Polsky et al., 2009). Children's early participation in Medicaid improves their long-term health (Boudreaux et al., 2016). Medicaid expansion reduces the mortality rate of children and infants (Currie & Gruber 1996, Currie & Gruber 1996), but it has little effect on the current health status of older children (Currie et al., 2008).

The expansion and development of health insurance in China, a developing country, has also had mixed health outcomes. A study investigates a community-based health insurance program in the western provinces of China from 2003 to 2006 and finds that the program enhanced the health status of local citizens (Wang et al., 2009). Through a quasi-experimental approach, the literature explores the relationship between NCMS and the health status of the rural Chinese population, concluding that NCMS has a limited effect on health status (Liang et al., 2012). Using data from the 2006 China Agricultural Census (CAC) and a Difference-in-Differences propensity score method, one study discovers that the implementation of NCMS does not affect child or maternal death because most of the differences are caused by the NCMS's endogenous introduction and adoption (Chen & Jin, 2012).

In summary, there is no consensus in the existing literature on the impact of health insurance on health. This study adds new evidence that health insurance can influence health. Second, most of the literature in China has examined changes in the health status of uninsured and insured patients. The impact of supplemental health insurance on population health is the subject of this study. It is also the first study to examine the effect of CII on health. Additionally, we employed a DiD with multiple time periods approach that takes into account the staggered implementation of CII across cities and treatment effect heterogeneity, thus further complementing the literature.

Data and Summary Statistics

Data

Given the city rollout of the CII, our analysis requires data with information on older adults' health outcomes, family information, health care and insurance, biomarkers, as well as demographic background. We use the same data as in Chapter One with 52,521 observations, focusing on older adults respondents over 45 years of age and excluding those not registered with URMI, NCMS, or URRMI.

Health Indicators

We use multiple health indicators to measure older adults' health, including health index (excluding metabolic index of obesity), self-reported health, and activities of daily living (ADL) limitation. CHARLS respondents report their height and weight (thus determining obesity[10]) and whether they have been diagnosed with hypertension, diabetes, or heart disease/attack. These data allow us to calculate the metabolic syndrome index. However, since CHARLS did not collect the height and weight of the respondents in 2018, we could not calculate the body mass index of the respondents in 2018. Therefore, we constructed a health index, which is a metabolic syndrome index excluding obesity, based on the data of four waves. Health indices are

[10] Obesity is defined as having a body mass index (BMI, one's weight (kg) divided by the square of height (m)) of 25 or more (classified according to Asian BMI measurement).

constructed as the equally-weighted average across each component's z-score. Subtraction of the mean and division by the standard deviation yields the z-score. In the case of metabolic syndrome, once diagnosed (=1), all components represent "bad" (hypertension, diabetes, heart disease/attack), so the increase in the metabolic syndrome index indicates a worse outcome.

Based on the question "Would you say your health?", we construct three binary variables of self-reported health status, which are good or very good, fair, and poor or very poor.[11] The value of each variable is set to 1 if the answer was "yes" and to 0 otherwise.

For ADL limitation, we extracted 6 items from the CHARLS that measured levels of independence for dressing, bathing, eating, bedding, toilet use, and controlling urination and defecation. Each ADL item's response was recorded as 0 if the respondent had no problems with the activity or 1 if the respondent reported any difficulty with the activity or was unable to complete it. Thus, the ADL measure overall score goes from 0 to 6, with a lower number indicating greater performance.

Control Variables

We control for demographic and socioeconomic covariates that may affect enrollment in the URMI, NCMS, as well as health outcomes, including age, gender, marital status (1 = married), education level, hukou, family size, GDP per capita, and urbanization rate.

Descriptive Analysis for Health Outcomes

As in chapter one, due to the different times of intervention in different cities, we divided the samples into four groups: group 2013, group 2015, group 2018, and group not-implemented

[11] We combine the answers "very good" and "good" into a binary variable "good", and the answers "very poor" and "poor" into the binary variable "poor".

(group 0). Table 2.1 provides a description of the panel sample and presents the health outcomes of each group before the policy intervention (2011). Generally, Self-reported health as fair is relatively balanced in the sample, at 48%. 22% of the older adults in the sample rated their health as very good and good, while 30% rated their health as poor and very poor. The weighted mean of the health index (including hypertension, adult-onset diabetes, and heart disease/heart attack) is -0.026. The rate of being diagnosed with hypertension is relatively high, which is 24%. The approximate average ADL difficulty is 0.394.

Table 2.1. Summary Statistics of Health Outcomes before Intervention.

	Group 2013	Group 2015	Group 2018	Group 0	Total	Min	Max
Self-reported health							
Very good or good[12]	0.254	0.208^{***}	0.222^{***}	0.145^{***}	0.220	0	1
	(0.435)	(0.406)	(0.416)	(0.353)	(0.414)		
Fair	0.462	0.487^{**}	0.480	0.488	0.480	0	1
	(0.499)	(0.500)	(0.500)	(0.500)	(0.500)		
Very poor or poor[13]	0.284	0.304^{**}	0.298	0.367^{***}	0.300	0	1
	(0.451)	(0.460)	(0.458)	(0.483)	(0.458)		
Health index	-0.007	-0.032^{*}	-0.072^{***}	0.236^{***}	-0.026	-0.560	3.121
	(0.661)	(0.627)	(0.604)	(0.856)	(0.640)		
Hypertension	0.261	0.247	0.208^{***}	0.286	0.244	0	1
	(0.439)	(0.431)	(0.406)	(0.453)	(0.429)		
Diabetes	0.056	0.050	0.039^{***}	0.063	0.050	0	1
	(0.231)	(0.218)	(0.193)	(0.243)	(0.217)		
Heart disease	0.107	0.103	0.105	0.318^{***}	0.111	0	1
	(0.309)	(0.305)	(0.307)	(0.466)	(0.314)		
ADL limitation	0.395	0.410	0.362	0.310	0.394	0	6
	(1.086)	(1.073)	(1.017)	(0.957)	(1.062)		
Number of observations	3124	7284	2649	406	13463		

Source: CHARLS 2011. *Notes:* T-test was used to assess the differences in variables between group 2013 and the other three groups in 2011. ***, ** and * denote statistical significance at 0.01, 0.05, and 0.10 levels, respectively.

[12] This variable is combined by the answer “very good” and “good”.
[13] This variable is combined by the answer “very poor” and “poor”.

Empirical Framework

We use the same method described in Chapter One with health outcomes as the dependent variables, that is, Callaway and Sant'Anna's (2020) Difference-in-Differences with multiple time periods method. This method enables us to evaluate whether the effect of CII on health outcomes changes over time and accounts for variation in the timing of CII implementation across cities. As in Chapter One, we define treated groups by the time period when they first implemented CII. We consider the case where “not-yet-treated” cities as the comparison group and use the doubly robust (DR) form as an estimator. We present aggregated treatment effects, including the average treatment effects that vary with the duration of treatment exposure, the average treatment effects that vary across groups, and the cumulative average treatment effects of the policy across all groups until time *t*.

Results

Group-time Average Treatment Effects

Figure 2.1 reports the coefficients of group-time average treatment effects for the CII exposure variable in health outcomes models for each group described above, along with a simultaneous 95% confidence band. Appendix Table 7 presents the coefficient estimates and confidence intervals corresponding to this graph. Each set of results comes from models that include the complete set of demographic controls and prefecture city level effects. The group-time average treatment effect estimates provide support for the view that the CII has significantly decreased the middle-aged and older adults’ ADL limitations and can lead to an increased probability of “good” or “very good” health. As can be seen in the figure, none of the pre-treatment coefficient estimates are statistically significant for all health outcomes. The p-value

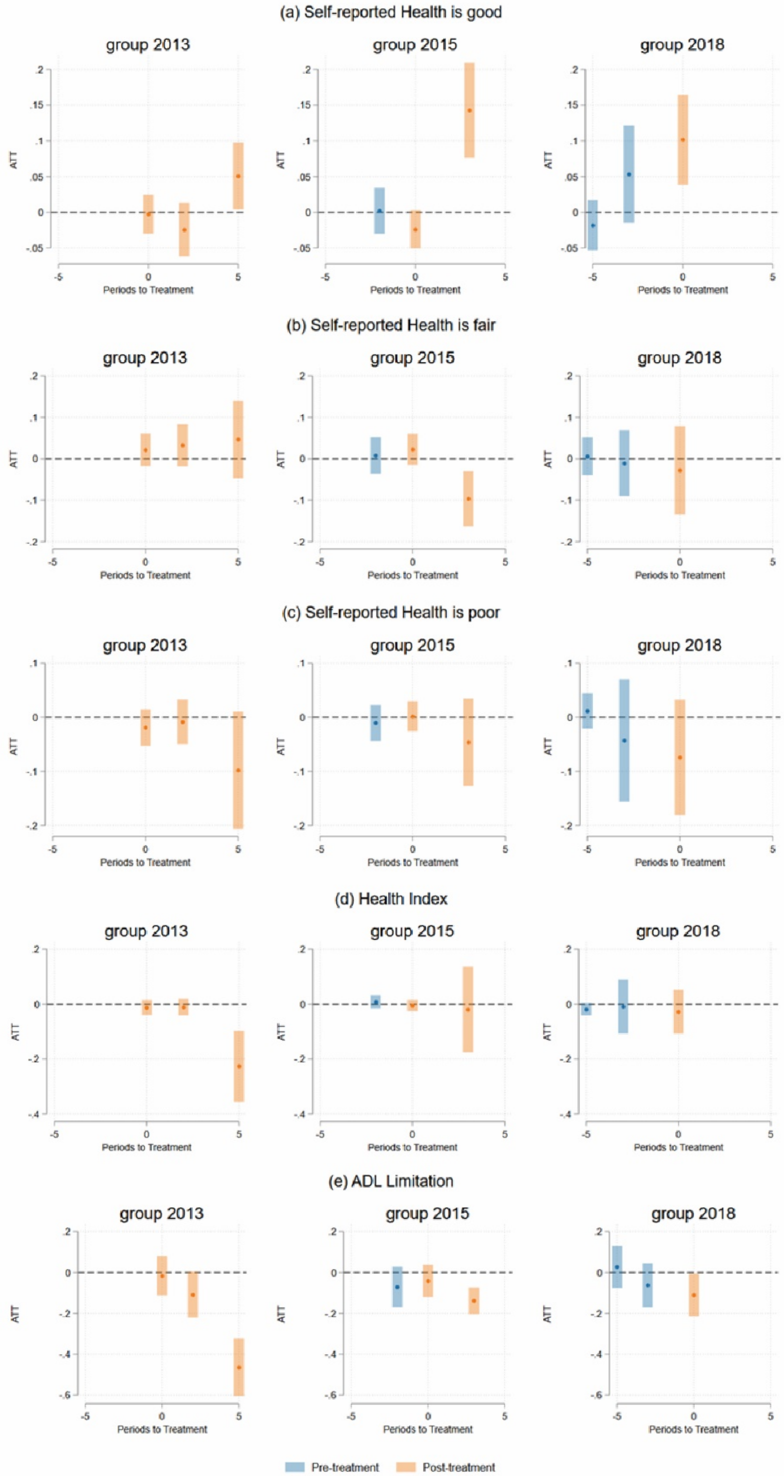

Figure 2.1. CII Group-time Average Treatment Effects on Health Outcomes.

Notes: The effect of the CII on "good" or "very good" health is Panel (a), "fair" self-reported health is Panel (b), "poor" or "very poor" health is Panel (c), health index is Panel (d), and ADL limitations is Panel (e). Blue plots give point estimates and simultaneous 95% confidence intervals for the prefecture city level pre-treatment period clustering. These should be equal to zero under the null hypothesis of the parallel trends assumption holding in all periods. Orange plots provide point estimates and simultaneous 95% confidence intervals for the treatment effect of implementing CII clustering at the prefecture city level. The estimates use the doubly-robust estimator.

for the joint test of zero pre-treatment effects is 0.12 for “good” or “very good” health, 0.88 for “fair” health, 0.78 for “poor” or “very poor” health, 0.37 for health index, and 0.29 for ADL limitation. Specifically, three post-treatment effects are significantly different from 0 for “good” or “very good” health, and four post-treatment effects are significantly different from 0 for ADL limitations. In addition, the CII take-up status has little impact on the “fair” and “poor” or “very poor” health, and health index.

Aggregated Treatment Effects

Table 2.2 represents CII aggregated treatment effect estimates for health outcomes. These parameters provide a similar picture to the group-time average treatment effects. The estimate for the simple weighted average treatment effect shows that the CII policy improves the probability of “good” or “very good” health by 0.04 for the treated group relative to the control group. The treatment effect is more significant for group 2015 and group 2018, while the treatment effect is not significant for group 2013. According to the event study, the longer the exposure time, the greater the improvement in self-rated health. Moreover, we find a 0.033 decrease in “poor” or “very poor” health after the CII adoption. However, no group is significant in terms of the group-specific average treatment effects. We find a 5.1 percentage point increase in the probability of reporting good or very good health, 9.8 percentage point decrease (significant at the 10% level) in the probability of reporting poor or very poor health and 0.227 decrease in the metabolic health index five years following the implementation of CII.

For the aggregated treatment effect on having ADL limitations (see Panel (e) of Table 2.2), the weighted mean of the group-time averaged treatment effects (by group size) for all available groups is -0.127. The areas where the CII policy was implemented in 2013 have the greatest reduction in ADL limitations. The impact of implementing CII on reducing ADL limitations is positive, and the longer the city is exposed to the policy, the greater the impact. In terms of calendar time effects, the cumulative average treatment effects are significant in 2015 and 2018 among individuals who have been treated. In addition, the CII implementation has a limited impact on "fair" health and health index[14]. Overall, these results suggest that the CII improved health and led to significant health improvements over time, which may explain the reductions in hospitalizations five years after implementation and may result in cost savings over the long term.

Table 2.2. CII Aggregated Treatment Effect Estimates on Health Outcomes.

	Aggregated Treatment Effects			
(a) Self-reported health is good or very good				
Simple weighted average	0.040^{***}			
	(0.013)			
Group-specific effects	Group 2013	Group 2015	Group 2018	
	0.007	0.053^{***}	0.102^{***}	
	(0.015)	(0.018)	(0.032)	
Calendar time effects	T=2013	T=2015	T=2018	
	-0.002	-0.024^{*}	0.110^{***}	
	(0.014)	(0.012)	(0.023)	
Event study	T+0	T+2	T+3	T+5
	0.004	-0.024	0.143^{***}	0.051^{**}
	(0.012)	(0.019)	(0.034)	(0.024)
(b) Self-reported health is fair				
Simple weighted average	-0.007			
	(0.016)			
Group-specific effects	Group 2013	Group 2015	Group 2018	
	0.033	-0.032^{*}	-0.028	
	(0.024)	(0.020)	(0.055)	
Calendar time effects	T=2013	T=2015	T=2018	
	0.022	0.025	-0.045^{*}	
	(0.020)	(0.016)	(0.026)	
Event study	T+0	T+2	T+3	T+5

[14] We also look at the effect on the metabolic syndrome index. However, it is not significant because of the small sample size and the unavailability of data for 2018.

Table 2.2 (Continued)

	Aggregated Treatment Effects			
	0.013	0.033	-0.096***	0.047
	(0.015)	(0.026)	(0.034)	(0.048)
(c) Self-reported health is poor or very poor				
Simple weighted average	-0.033**			
	(0.017)			
Group-specific effects	Group 2013	Group 2015	Group 2018	
	-0.041	-0.020	-0.074	
	(0.026)	(0.019)	(0.054)	
Calendar time effects	T=2013	T=2015	T=2018	
	-0.019	-0.001	-0.065**	
	(0.017)	(0.012)	(0.032)	
Event study	T+0	T+2	T+3	T+5
	-0.017	-0.008	-0.046	-0.098*
	(0.013)	(0.021)	(0.041)	(0.056)
(d) Health index[15]				
Simple weighted average	-0.039			
	(0.028)			
Group-specific effects	Group 2013	Group 2015	Group 2018	
	-0.082***	-0.012	-0.027	
	(0.021)	(0.040)	(0.041)	
Calendar time effects	T=2013	T=2015	T=2018	
	-0.012	-0.007	-0.075	
	(0.014)	(0.009)	(0.057)	
Event study	T+0	T+2	T+3	T+5
	-0.011	-0.011	-0.019	-0.227***
	(0.010)	(0.015)	(0.080)	(0.066)
(e) ADL limitation[16]				
Simple weighted average	-0.127***			
	(0.025)			
Group-specific effects	Group 2013	Group 2015	Group 2018	
	-0.192***	-0.086***	-0.110**	
	(0.044)	(0.027)	(0.054)	
Calendar time effects	T=2013	T=2015	T=2018	
	-0.016	-0.061*	-0.217***	
	(0.049)	(0.034)	(0.033)	
Event study	T+0	T+2	T+3	T+5
	-0.047*	-0.108*	-0.138***	-0.464***

[15] We construct a health index based on whether the respondents have been diagnosed with hypertension, diabetes, or heart disease/attack. Health indices are constructed as the equally-weighted average across each component's z-score.

[16] ADL limitation includes that measured levels of independence for dressing, bathing, eating, bedding, toilet use, and controlling urination and defecation.

Table 2.2 (Continued)

	(0.028)	(0.058)	(0.033)	(0.072)

Data source: 2011-2018 waves of CHARLS. *Notes:* The table reports the aggregate treatment effect parameters for "good" or "very good" health in Panel (a), "fair" self-reported health in Panel (b), "poor" or "very poor" health in Panel (c), health index in Panel (d), and ADL limitation in Panel (e), along with prefecture city level clustering. The "Simple Weighted Average" row reports the weighted mean of the group-time averaged treatment effects (by group size) for all available groups. The "Group-Specific Effects" row summarizes the average treatment effects by the time of CII implementation; here, g indicates the year in which a city was first treated. The "Event Study" row reports the average treatment effect of exposure to CII implementation; here, e indicates the time of exposure to treatment. The "Calendar Time Effect" row reports the average treatment effect by year; t indicates the annual index. The estimates use the doubly robust estimator. ***, ** and * denote statistical significance at 0.01, 0.05, and 0.1 levels, respectively. Sample size: 52,521 observations. Covariates: age, male, education level, marriage, family size, agricultural hukou, nonagricultural hukou, unified hukou, per capita GDP and urbanization rate.

Heterogeneity Analysis

To further explore the heterogeneity of the impact of CII on the health of middle-aged and older residents, the sample is grouped by different age groups, income groups, and urban and rural residents, as described in Chapter 1, and re-estimated the regression, and the results are presented in Table2.3. The CII implementation has a positive effect on rural residents. Specifically, "good" or "very good" health increases and ADL limitations decrease, and both are significant at the 1 percent level. The coefficient of health index and "poor" or "very poor" health is decreased, and the effects are significant at the 10 percent level. For urban residents, there is no significant improvement. In the heterogeneity analysis in the first chapter, we find a significant increase in the number of hospitalizations among rural residents. This may be since rural residents are relatively disadvantaged in terms of human capital and healthcare benefits, and therefore the CII system has a greater effect on improving access to health care services for rural residents, promoting the release of demand for health care services, and improving their health.

In addition, there is a significant improvement in the health of the 60+ age group. The coefficients of "good" or "very good", "poor" or "very poor" health, and ADL limitations are significant for older adults. In the heterogeneity analysis in the first chapter, we find a significant increase in the number of hospitalizations among older adults. This is because the implementation of CII has made sick seniors more willing to go to the hospital for treatment.

The combined effect of the CII implementation on residents with different incomes shows that CII has mainly improved the health of the middle-income group. Specifically, the coefficient for “good” or “very good” health increases, and the coefficients for health index and ADL limitations decrease after the adoption of the CII. For middle-income residents, they are more likely to reach the threshold of CII when they fall ill. The CII reduces the price of medical services for residents, especially inpatient medical services by a price subsidy mechanism. Therefore, it helps to release the demand for inpatient medical services for the middle-income group, and thus the health improvement effect for the middle-income group is more obvious.

Table 2.3. Results of Heterogeneity Analysis on Health Outcomes.

Variables	Rural	Urban	Middle-aged	Older	Low income	Middle income	High income
Self-reported health							
Good or very good	0.042^{***}	0.460	0.036^{***}	0.043^{***}	0.058^{**}	0.092^{*}	0.014
	(0.014)	(0.777)	(0.017)	(0.014)	(0.024)	(0.049)	(0.038)
Fair	-0.010	0.309	-0.040^{*}	0.021	-0.013	0.035	-0.014
	(0.018)	(0.748)	(0.024)	(0.022)	(0.031)	(0.058)	(0.049)
Poor or very poor	-0.033^{*}	-0.769	0.004	-0.064^{***}	-0.046	-0.128	0.000
	(0.017)	(1.519)	(0.016)	(0.020)	(0.031)	(0.084)	(0.037)
Health index	-0.040^{*}	-0.755^{***}	0.009	0.026	0.058	-0.117^{**}	-0.179^{***}
	(0.023)	(0.250)	(0.024)	(0.022)	(0.044)	(0.058)	(0.045)
ADL limitation	-0.120^{***}	-0.112	0.012	-0.287^{***}	-0.187^{**}	-0.272^{***}	-0.123^{**}
	(0.043)	(0.105)	(0.044)	(0.048)	(0.092)	(0.088)	(0.049)
N	49345	3176	25053	27468	17236	17223	17223

Data source: 2011-2018 waves of CHARLS. *Notes:* The table reports the simple weighted average treatment effects of heterogeneity analysis for health outcomes. The estimates use the doubly robust estimator. ***, ** and * denote statistical significance at 0.01, 0.05, and 0.1 levels, respectively. Covariates: age, male, education level, marriage, family size, agricultural hukou, nonagricultural hukou, unified hukou, per capita GDP and urbanization rate.

Robustness Check

Through DID with multiple time periods regression analysis, we find that CII implementation is effective in improving residents' "good" or "very good" health and reducing ADL limitations. To further test the reliability of the regression results, we performed a robustness check using the same method as in Chapter 1 and the results are shown in Table 2.4. Simple weighted average treatment effects in all three robustness tests showed that the implementation of CII improves the "good" or "very good" health and decreases ADL limitations of the sample. This means that the empirical results are robust. In addition, the treatment effect of "poor" or "very poor" health is not significant when we excluded the sample that enrolled in the URRMI. There is no significant effect of CII implementation on "fair" self-reported health and health index.

Table 2.4. Robustness Check on Health Outcomes.

Variables	Without other health insurance	Without URRMI	Grouping using interview dates
Self-reported health			
Good or very good	0.039^{***}	0.023^{**}	0.041^{***}
	(0.012)	(0.010)	(0.013)
Fair	0.003	-0.003	-0.008
	(0.016)	(0.018)	(0.016)
Poor or very poor	-0.042^{***}	-0.020	-0.033^{**}
	(0.016)	(0.016)	(0.017)
Health index	-0.046	-0.026	-0.039
	(0.029)	(0.037)	(0.028)
ADL limitation	-0.143^{***}	-0.113^{***}	-0.135^{***}
	(0.034)	(0.035)	(0.033)
N	50011	49328	52521

Data source: 2011-2018 waves of CHARLS. *Notes:* The table reports the simple weighted average treatment effects of robustness check for health outcomes. The estimates use the doubly robust estimator. ***, ** and * denote statistical significance at 0.01, 0.05, and 0.1 levels, respectively. Covariates: age, male, education level, marriage, family size, agricultural hukou, nonagricultural hukou, unified hukou, per capita GDP and urbanization rate.

Placebo Test

Because CII applies to all urban and rural residents who participate in URMI, NCMS, or URRMI, we anticipate that residents who do not participate in URMI, NCMS and URRMI will be unaffected by CII. As a result, in this section, we employ doubly-robust DiD estimator regression on samples that did not participate in URMI, NCMS or URRMI, totaling 11,233 observations. Figure 2.2 presents coefficient estimates and simultaneous 95% confidence intervals from the group-time average treatment effects using the same model. Appendix Table 8 presents the coefficient estimates and confidence intervals corresponding to this graph. Table 2.5 presents the simple weighted average treatment effect estimates and p-value of pre-trend from the placebo test for different health outcomes. There is no evidence to suggest that the intervention has a significant effect on health outcomes for those who did not participate in the URMI, NCMS or URRMI. Although "poor" or "very poor" health has decreased, it is not statistically significant. We conclude that the CII has no positive effect on health outcomes for the samples without URMI, NCMS or URRMI enrollees.

Table 2.5. Placebo Test on Health Outcomes.

Variables	Simple weighted average	Pre-trend p-value
Self-reported health		
Good or very good	-0.044 (0.045)	0.322
Fair	0.078 (0.065)	0.634
Poor or very poor	-0.034 (0.041)	0.767
Health index	0.017 (0.046)	0.188
ADL limitations	-0.051 (0.053)	0.227
N	11233	

Data source: 2011-2018 waves of CHARLS. *Notes:* The table reports the simple weighted average treatment effects and p-value of the pre-trend of placebo test for health outcomes. The estimates use the doubly robust estimator. ***, ** and * denote statistical significance at 0.01, 0.05, and 0.1 levels, respectively. Covariates: age, male, education level, marriage, family size, agricultural hukou, nonagricultural hukou, unified hukou, per capita GDP and urbanization rate.

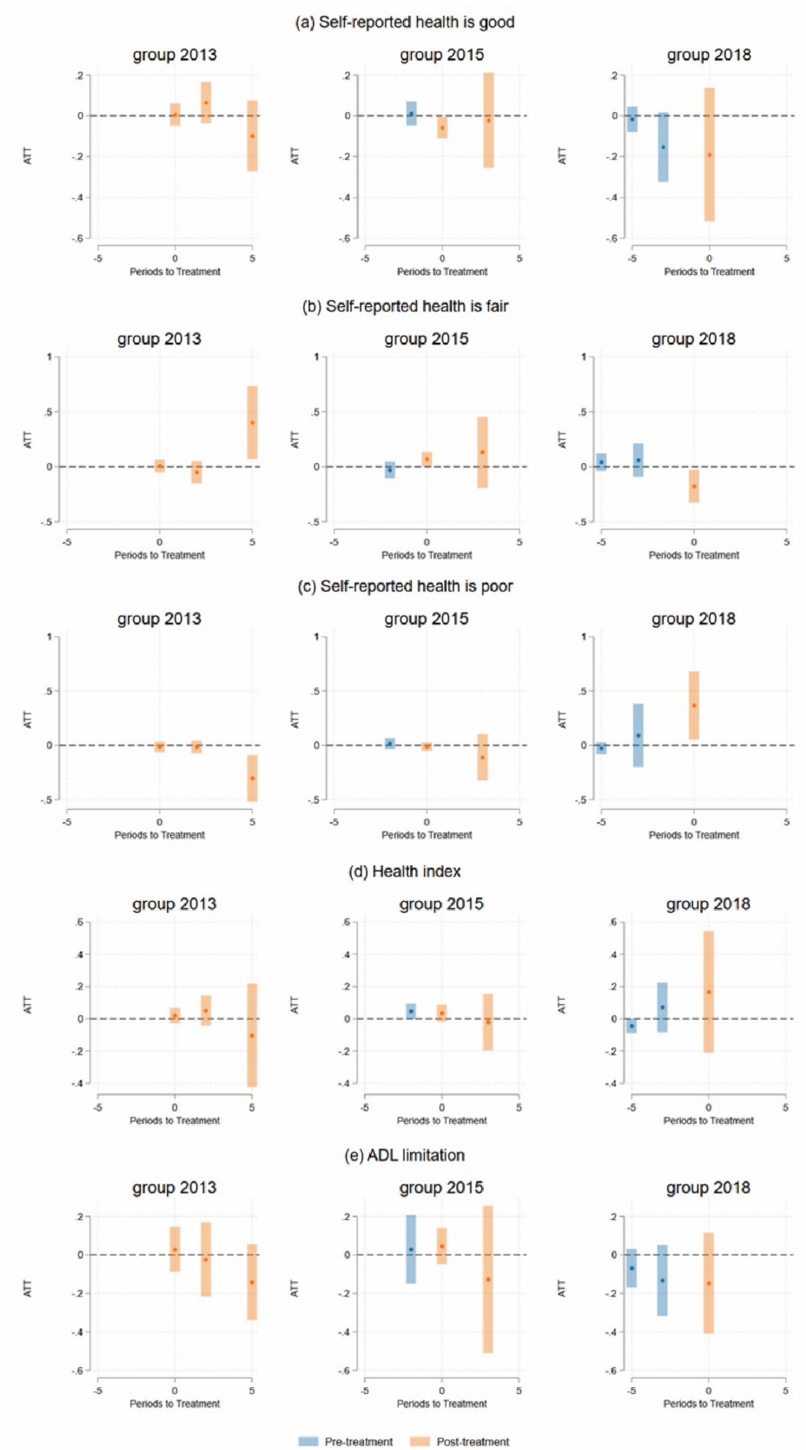

Figure 2.2. CII Group-time Average Treatment Effects on Health Outcomes of Placebo Test.

Conclusion

Using multiple time periods doubly-robust DID estimator, we investigate the impact of CII in improving health outcomes for middle-aged and older adults in China. The CII is probably more effective for middle-aged and older adults, who are more vulnerable to health risks and have more elastic healthcare demand. We discovered that CII participation has a significant positive impact on the reduction of ADL limitations and improvement of “good” or “very good” health. These results provide suggestive evidence for the hypothesis that the nonsignificant effect in utilization represents a shift towards care that is more efficient and a reduction in the use of unnecessary services. Analysis of heterogeneity shows that implementation of the CII increases the probability of reporting “good” or “very good” health for rural residents and low- and middle-income groups compared to urban residents and high-income groups and decreases the ADL limitations for rural residents and older groups compared to urban residents and middle-aged groups.

CHAPTER THREE:

THE IMPACT OF CRITICAL ILLNESS INSURANCE ON CONSUMPTION AND SAVINGS

Introduction

In recent years, China has gradually transformed its long-standing economic growth model, which relies on export trade and domestic investment, into a consumption-driven one. Stimulating consumption to increase domestic demand has become a key engine to drive economic growth. However, Chinese households generally have the problem of under-consumption and high savings. From 1998 to 2010, the savings rate of urban and rural residents rose from 20% to 30% and 26% respectively for urban and rural residents. At the same time, the consumption rate also showed a declining trend from 46.48% to 33.22% (Ling & Zhang, 2012). Multiple factors contribute to China's low consumption and high savings rate, including the widening income difference between urban and rural areas, income uncertainty, and the absence of investment avenues on the financial market. However, some scholars have suggested that a series of social welfare system reforms including housing, education, health care security, and pension system that started in the 1980s have increased the uncertainty of residents' future, while these social welfare systems generally should reduce residents' uncertainty (Wang 2008, Wang & Gong 2007). Therefore, the key to improve wellbeing of consumer individuals is how to improve the social security system. One way is to increase welfare by improving their health status, which we discussed in Chapter 2. Another way is to increase consumption and reduce the need for precautionary savings. Due to the presence of future uncertainties, households reduce current consumption and increase precautionary savings to protect themselves against future risks. Since health expenditures are ongoing and generally increase with age, they have a significant impact on the uncertainty of a household's future financial condition. By reducing uncertainty about future spending on health services and reducing the health risks that residents may face, the introduction of health insurance may reduce the need for precautionary savings and promote consumption.

In August 2012, the Chinese government introduced the critical illness insurance (CII) pilot project as a supplement to the New Rural Cooperative Medical Scheme and Urban Residents Medical Insurance. CII system is established by allocating a certain proportion of funds from NCMS and URMI funds, and subsequently a dual medical insurance system of "basic medical insurance and critical illness insurance" has been established for urban and rural residents. The CII scheme has effectively decreased out-of-pocket inpatient expenses and improved the health of middle-aged and older residents. Can the CII system further mitigate health concerns and promote consumption? the existing research on this issue is limited.

This chapter aims to determine whether the implementation of CII stimulates consumption and enhances the well-being of middle-aged and older adults. We use the doubly-robust Difference-in-Differences estimator proposed by Callaway and Sant’anna (2020) to account for heterogeneous treatment effects and the staggered implementation of CII across regions in China. We further verify the reliability of the estimation results by placebo test and robustness check.

Literature Review

The theory of "precautionary savings" suggests that when people face uncertainty in future, they tend to save more and consume less in order to cope with the negative shock of uncertainty risk (Leland, 1978). Carroll et al. (1992) and Carroll (1994) found that an increase in future income uncertainty would significantly reduce current consumption levels. Atella et al. (2005), based on data from an Italian sample, find that uncertainty about future health care expenditures motivates households to increase precautionary savings against health care risks. Health insurance, as a risk transfer mechanism, can reduce the financial shock caused by the uncertainty of health care expenditures in the future, and therefore, to some extent, reduce people's incentive for precautionary savings.

Some empirical studies examine the impact of health insurance on household savings and consumption in different countries and deliver mixed evidence. Gruber & Yelowitz (1999) and Clark & Mitchell (2014) provide evidence that people with health insurance hold less wealth and more consumption. One study assesses the effect of Medicaid on households savings and finds that the disincentive effect is concentrated among the middle net-worth households but has no effect on low- and high-net-worth households, and it also has a spend down effect because it is means tested (Maynard & Qiu, 2008). In developing regions, related research is still in its early stages. Wagstaff & Pradhan (2005) find that the introduction of health insurance in Vietnam increased non-medical consumer spending. Chou et al. (2003) prove that the National Health Insurance (NHI) in Taiwan reduced household savings and that it had the largest negative impact on savings in the bottom quintile. In contrast, Kuan & Chen (2011) present different findings in studying the crowd-out effects[17] of NHI on household precautionary saving in Taiwan. They illustrate that high savers tend to have greater reductions in savings after the implementation of

[17] The crowd-out effect on household precautionary saving is to restrain residents' savings.

the NHI.

In recent years, there is some empirical research on the relationship between health insurance and residents' consumption in mainland China, and the results are mixed. Based on rural data from 2003 to 2006, Bai & Wu (2014) find that the NCMS increased households non-medical expenditure consumption by more than 5 percentage points. This effect is more significant among households with lower incomes or poorer health status. Cheung & Padieu (2015) suggest that NCMS has a negative impact on middle-income savings, but it has no impact on the poorest participants. Based on the panel data of 2007 and 2008, a Chinese study empirically analyzed the impact of URMI on urban household consumption using DID and FE methods. The econometric results show that the annual non-medical consumption expenditure of insured families is about 13% higher than that of uninsured families, and medical consumption has not changed significantly (Zang et al., 2012). Atella et al. (2015) concludes that the introduction of health care reform in China in 1998 increases the savings rate of low-income individuals in good health.

The literature on the impact of CII on consumption is still very limited. Zhao (2019) uses the data from the China Family Panel Studies (CFPS) in 2009, 2011 and 2013 and a DID approach to show that the CII program led to an increase in daily household consumption but not in household health expenditures for rural residents. A Chinese study by Gao & Ding (2021) uses data from the 2012 and 2014 China Labor Force Dynamics Survey (CLDS) and finds that the adoption of the CII increases rural household consumption by 4.25% and increases the share of non-medical consumption.

We provide new evidence on the impact of the Critical Illness Insurance program on older adults’ consumption. We collect more detailed information on the timing of implementation across prefectures in China compared to previous studies, which have examined province level variation in the timing of implementation (Zhao 2019) or have focused on rural residents (Zhao 2019, Gao & Ding 2021). We build on this literature by using a Difference-in-Differences estimator to identify causal effects. Our approach also accounts for the staggered implementation of the program across regions and potential heterogeneity in treatment effects.

Data and Summary Statistics

Data

Since this study is conducted based on the prefecture cities pilot characteristics of the CII, the construction of treatment groups required precision to the prefectures where the samples were located. Our analysis requires data with information on older adults' household consumption, household saving, family information, health care and insurance, as well as demographic background. We investigate the impact of the CII on household consumption, using the same data (52,521 observations, 13,280 individuals) as the first Chapter, focusing on older adults respondents over 45 years of age and excluding those who are not registered with URMI, NCMS, or URRMI.

Variables

The CHARLS survey of middle-aged and older households' consumption includes three components: weekly household consumption, monthly household consumption, and annual household consumption. The total household consumption comprises the total expenditure of the family for a year, which is the sum of these three parts of consumption expenditure. To comprehensively analyze the influence of the CII on the consumption of middle-aged and older families, we also examine non-medical expenditure and food expenditure.[18] In addition, household saving is the difference between annual household income and annual household consumption. All expenditure variables are adjusted for inflation using the Consumer Price Index published by the National Bureau of Statistics of China and setting 2010 as the base year.

We control for demographic and socioeconomic covariates that may affect enrollment in the URMI and NCMS, including age, gender, marital status, education level, hukou, family size, GDP per capita, and urbanization rate.

Descriptive Analysis for Consumption and Savings

As in chapter one, due to the different times of intervention in different cities, we divided the samples into four groups: group 2013, group 2015, group 2018, and group not-implemented (group 0). Table 3.1 presents the descriptive statistics of the baseline sample for consumption. Before the policy implementation, the per capita household consumption, per capita non-medical consumption, and per capita food consumption in group 2013 are higher than in group 2015. Savings per capita in the regions implementing the policy in 2018 are significantly higher than in other regions and are positive.

Table 3.1. Summary Statistics of Household Consumption and Savings before Intervention.

	Group 2013	Group 2015	Group 2018	Group 0	Total	Min	Max
Household consumption	7426.235 (11061.427)	6790.712*** (9133.547)	7631.887 (10248.045)	6472.110 (5098.379)	7104.373 (9774.425)	0	239128.800
Non-medical consumption	6449.634 (10215.267)	5844.028*** (7681.553)	6643.291 (8602.000)	5351.292* (3879.735)	6137.214 (8463.729)	0	239128.800
Food consumption	3184.036 (7472.679)	2822.663*** (4109.974)	3139.337 (3845.270)	2341.774** (2143.346)	2955.150 (5012.457)	0	229798.000

[18] We also analyze the impact of CII on medical expenditure and non-food consumption, but since their effects are not significant, we will not discuss them here.

Table 3.1 (Continued)

	Group 2013	Group 2015	Group 2018	Group 0	Total	Min	Max
Saving	-818.533 (15613.095)	-653.824 (23583.657)	275.815*** (13835.336)	-1322.429 (7859.149)	-519.214 (19858.916)	0	1146387.000
N	3124	7284	2649	406	13463		

Source: CHARLS 2011. *Notes:* Non-medical consumption is total household consumption minus household medical expenditures. Here, household medical expenses include direct or indirect medical expenses. Indirect medical expenses include transportation expenses, nutrition expenses, and family companionship expenses incurred for medical treatment. T-test was used to assess the differences in variables between group 2013 and the other three groups in 2011. ***, ** and * denote statistical significance at 0.01, 0.05, and 0.10 levels, respectively.

Results

Group-time Average Treatment Effects

We used Callaway and Sant'Anna's (2020) Difference-in-Differences with multiple time periods method as described in Chapter One. Similarly, we define the treatment group in terms of the time periods when CII was first implemented, include "not yet treated" prefectures as a comparison group, and use a doubly robust (DR) form as an estimator. This method enables us to exploit variation in the timing of CII implementation across prefecture cities to estimate the causal impact of the insurance program on consumption and savings. To avoid possible estimation bias due to extreme values, the main variables were Winsorized and the proportion was set to 1%. We first present coefficient estimates and simultaneous 95% confidence intervals from the group-time average treatment effects for savings and three types of consumption expenditures in Figure 3.1. Appendix Table 9 presents the coefficient estimates and confidence intervals corresponding to this graph. These household consumption and savings are presented in per capita terms. Each set of results comes from models that include the complete set of demographic controls and prefecture city level effects. As can be seen in the figure, for all consumption outcomes, none of the pre-treatment coefficient estimates are statistically significant under conditional parallel trends assumption. The p-value for the joint test of zero pre-treatment effects is 0.62 for per capita total household consumption, 0.60 for per capita non-medical consumption, 0.27 for per capita food consumption, and 0.18 for per capita saving. We cannot reject the joint null hypothesis that all pre-treatment effects are equal to zero.

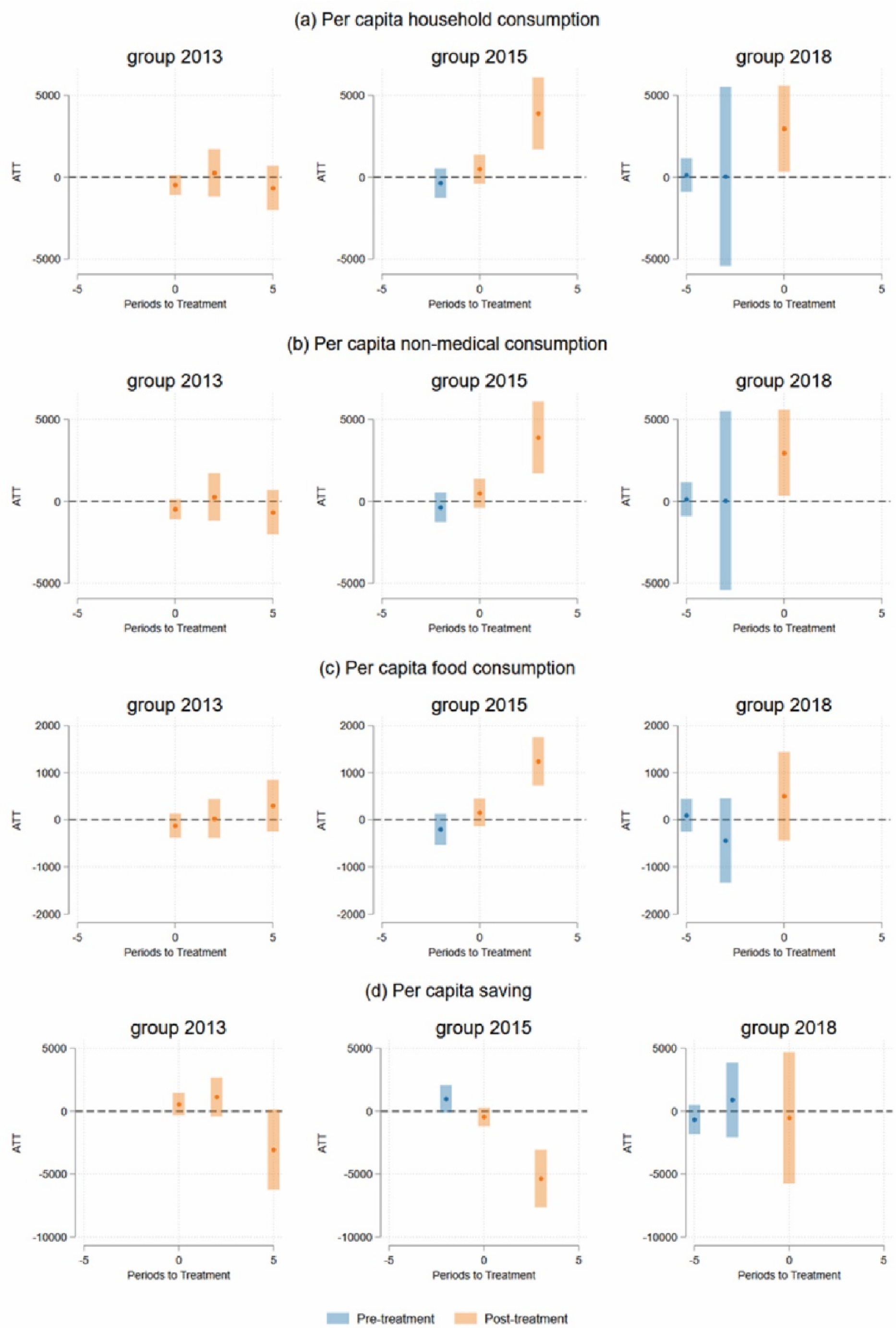

Figure 3.1. CII Group-time Average Treatment Effects on Consumption and Savings.
Notes: The effect of the CII on per capita household consumption is Panel (a), per capita non-medical consumption is Panel (b), per capita food consumption is Panel (c), and per capita saving is Panel (d).

Aggregated Treatment Effects

Table 3.2 reports the treatment effect of CII on consumption and savings outcomes aggregated in various ways under the conditional parallel trends assumption. From Table 3.2, we find statistically significant effect on saving and four other kinds of consumption. Specifically, the estimate for the simple weighted average treatment effect shows that the CII policy increases per capita household consumption by CNY 1278.098, compared to 2011, increased by 18% in the treatment group. This finding is comparable to Zhao's (2019) conclusion (significant increase of 15%), but the effect coefficient is slightly larger in our study. The reason for this could be that our sample has data from 2018, and the largest and statistically significant effect is reached in 2018, as seen in the calendar time effects results. We also find evidence of heterogeneous treatment effects under conditional parallel trends - regions that adopted CII in 2015 and 2018 experienced larger and statistically significant increases in household total consumption while areas that expanded in 2013 does not experience a statistically significant increase in household total consumption. We also find that the stimulus effect of the CII program on consumption remains significant for non-medical consumption. The pre vs post change in household non-medical consumption for the treated groups is CNY 873.649 higher than the pre vs post change for the control group. Medical insurance is used to affect medical expenses by reducing medical expenses paid for by the population. The considerable increase in non-medical consumption supports the idea that the CII program's stimulating effect on consumption results from the decline in precautionary savings. We also find a CNY 438.504 increase in household food consumption after the CII adoption but only residents in areas that implemented CII in 2015 experienced a significant increase in household food consumption. We find that the CII program significantly decreased per capita saving by CNY 1752.614 (simple weighted average). We find a larger decrease in saving for regions that implemented CII in 2015 compared to regions that implemented CII in 2013 (CNY 2864.151 versus CNY 519.029), suggesting that treatment effects are heterogeneous across groups. The decrease in savings after 5 years of exposure to CII is CNY 3057.016 compared to a decrease of CNY 190.791 in the year of CII implementation. This confirms that the introduction of the CII program reduces household savings and increases household consumption.

Table 3.2. CII Aggregated Treatment Effect Estimates on Consumption and Savings.

	Aggregated Treatment Effects			
(a) Per capita household consumption				
Simple weighted average	1278.098***			
	(435.095)			
Group-specific effects	Group 2013	Group 2015	Group 2018	
	-310.214	2189.102***	2959.672**	
	(365.872)	(579.466)	(1343.722)	
Calendar time effects	T=2013	T=2015	T=2018	
	-471.647	420.838	2421.675***	
	(310.550)	(426.351)	(824.170)	
Event study	T+0	T+2	T+3	T+5
	687.746*	263.438	3902.897***	-669.119
	(395.052)	(741.111)	(1121.583)	(689.830)
(b) Per capita non-medical consumption				
Simple weighted average	873.649***			
	(333.440)			
Group-specific effects	Group 2013	Group 2015	Group 2018	
	-363.356	1639.175***	1823.065*	
	(342.522)	(404.839)	(1075.516)	
Calendar time effects	T=2013	T=2015	T=2018	
	-446.436*	148.643	1799.309***	
	(247.792)	(376.329)	(588.974)	
Event study	T+0	T+2	T+3	T+5
	300.665	140.280	3144.606***	-737.060
	(330.809)	(638.811)	(703.152)	(741.914)
(c) Per capita food consumption				

Table 3.2 (Continued)

	Aggregated Treatment Effects			
Simple weighted average	438.504***			
	(115.912)			
Group-specific effects	Group 2013	Group 2015	Group 2018	
	72.706	685.985***	504.719	
	(130.396)	(167.423)	(477.668)	
Calendar time effects	T=2013	T=2015	T=2018	
	-124.466	116.762	847.789***	
	(131.300)	(137.950)	(178.050)	
Event study	T+0	T+2	T+3	T+5
	146.661	27.491	1243.766***	300.467
	(131.116)	(210.855)	(261.808)	(279.700)
(d) Per capita saving				
Simple weighted average	-1752.614***			
	(520.464)			
Group-specific effects	Group 2013	Group 2015	Group 2018	
	-519.029	-2864.151***	-524.846	
	(651.568)	(591.933)	(2667.293)	
Calendar time effects	T=2013	T=2015	T=2018	
	560.011	52.119	-3850.461***	
	(454.241)	(376.350)	(1026.023)	
Event study	T+0	T+2	T+3	T+5
	-190.791	1137.437	-5349.470***	-3057.016*
	(534.673)	(789.199)	(1161.421)	(1627.122)

Data source: 2011-2018 waves of CHARLS. *Notes:* The table reports the aggregate treatment effect parameters for per capita household consumption in Panel (a), per capita non-medical consumption in Panel (b), per capita food consumption in Panel (c), and per capita saving in Panel (d), along with prefecture city level clustering. The "Simple Weighted Average" row reports the weighted mean of the group-time averaged treatment effects (by group size) for all available groups. The "Group-Specific Effects" row summarizes the average treatment effects by the time of CII implementation; here, g indicates the year in which a city was first treated. The "Event Study" row reports the average treatment effect of exposure to CII implementation; here, e indicates the time of exposure to treatment. The "Calendar Time Effect" row reports the average treatment effect by year; t indicates the annual index. The estimates use the doubly robust estimator. ***, ** and * denote statistical significance at 0.01, 0.05, and 0.1 levels, respectively. Sample size: 52,521 observations. Covariates: age, male, education level, marriage, family size, agricultural hukou, nonagricultural hukou, unified hukou, per capita GDP and urbanization rate. Group 2013 refers to cities that began implementing the policy before July 2013. Group 2015 refers to cities that began implementing the policy from August 2013 to July 2015. Group 2018 refers to cities that began implementing the policy from August 2015 to July 2018.

Heterogeneity Analysis

The impact of CII on consumption and savings may vary by age, income, and rural residence. The previous analysis only reflects the effect of participation in CII on the consumption of the full sample of middle-aged and older households but does not account for their heterogeneity. This paper presents a heterogeneous analysis of the impact of CII participation on consumption from three perspectives: urban and rural area, age, and income, and is shown in Table 3.3. Rural and urban areas differ in terms of consumption levels and consumption habits, as well as basic medical insurance systems. To assess whether the effect of CII differs across these regions we stratify the total sample into urban and rural areas. As shown in the estimates in the first two columns of Table 3.3, the CII program significantly increased all consumption expenditures and reduced saving, but the results of urban samples are not significant. The disparity between rural and urban basic health insurance coverage capacity may account for this result. Most of the rural sample is enrolled in NCMS, which has substantially lower reimbursement rates and coverage than URMI and does not have the same capacity for coverage as URMI or the combined URRMI. Rural middle-aged and older households have, in theory, more preventative savings for medical treatment than urban households to withstand illness risk shocks (Bian & Li, 2021). The implementation of CII can reduce the uncertainty of medical expenditure due to future disease shocks and assist rural households release their precautionary savings, hence increasing their non-medical consumption.

The results in the third and fourth columns of Table 3.3 indicate that the CII program significantly increase total household consumption by CNY 881.041 and food consumption by CNY 243.934 and decrease saving by CNY 2204.729 among older adults (60+ years) but has no significant effect on consumption for middle-aged adults. The older population is under pressure from both lower incomes and increased health risks, so consumer demand will be restrained. The introduction of CII, while not having a direct impact on their income, can effectively mitigate the health risks they face thereby reducing precautionary savings. Therefore, the promoting effect of the CII program on the consumption of the older population is likely to be more sensitive.

We next analyze the response of households with different incomes to the CII policy, and the results are shown in the last three columns of Table 3.3. We find that the CII program significantly increase middle-income group's non-medical consumption by CNY 1670.849 and decrease saving by CNY 2018.756 at the 10% level. The CII program results has no significant effect on consumption and saving for the low-income group. For the treatment effect of high-income groups, CII intervention only significantly reduced their family savings at the level of 10%. High-income households are more resistant to the financial risks associated with illness, so their consumption behavior is less significantly affected by the CII program. For low-income residents, the starting threshold for the CII is high, usually at the local per capita disposable income of the previous year. The income of the low-income group cannot even reach this threshold, so the positive effect of the system is limited. The CII policy will therefore have a greater impact on the consumption of middle-income households.

Table 3.3. Results of Heterogeneity Analysis on Consumption and Savings.

Variables	Rural	Urban	Middle-aged	Older	Low income	Middle income	High income
Household consumption	1334.801***	2787.748	-28.539	881.041**	696.673	1853.815	884.742
	(383.748)	(3963.798)	(518.270)	(396.309)	(460.608)	(1171.190)	(1497.273)
Non-medical consumption	1008.346***	1521.465	47.974	377.260	499.886	1670.849*	368.631
	(350.463)	(1976.598)	(508.575)	(349.011)	(485.295)	(996.137)	(1429.961)
Food consumption	391.392***	-318.691	47.066	243.934*	-109.735	-196.296	-67.828
	(121.627)	(1324.222)	(224.725)	(145.632)	(275.511)	(293.009)	(281.371)
Saving	-1785.093***	-4989.369	1222.505	-2204.729**	-421.813	-2018.756*	-3112.945*
	(501.255)	(3207.360)	(799.813)	(910.092)	(385.186)	(1053.950)	(1668.809)
N	49345	3176	25053	27468	17236	17223	17223

Data source: 2011-2018 waves of CHARLS. *Notes:* The table reports the simple weighted average treatment effects of heterogeneity analysis for health outcomes. The variables are taken per capita value. The estimates use the doubly robust estimator. ***, ** and * denote statistical significance at 0.01, 0.05, and 0.1 levels, respectively. Covariates: age, male, education level, marriage, family size, agricultural hukou, nonagricultural hukou, unified hukou, per capita

GDP and urbanization rate.

Robustness Check

The following robustness tests are undertaken in this study to assess the reliability of the results regarding the impact of CII on household consumption. The regression results in this section were obtained by excluding those who were enrolled in other health insurance, excluding those who were enrolled in URRMI, and using the year and month in which respondents were interviewed to match the time of CII implementation for the subgroups, respectively. Simple weighted average treatment effects results are shown in Table 3.4. We find that the coefficients and significance of the effects of CII implementation on total household consumption, non-medical consumption, food consumption, and saving do not show substantial changes, which are basically consistent with the base measurement results, indicating that the empirical results are relatively robust.

Placebo Test

For the placebo test, we selected samples without registered URMI, NCMS or URRMI and re-estimated the regression results using the doubly-robust DID estimator. Since the CII program applies to both urban and rural people who engage in URMI, NCMS and URRMI, we expect that residents who do not participate in URMI, NCMS and URRMI will not be affected by the CII. Figure 3.2 presents coefficient estimates and simultaneous 95% confidence intervals from the group-time average treatment regression using the same model. Appendix Table 10 presents the coefficient estimates and confidence intervals corresponding to this graph. Table 3.5 demonstrates the simple weighted average treatment effect estimates and p-value of pre-trend of the placebo test for consumption and saving outcomes. According to the results of the placebo

Table 3.4. Robustness Check on Consumption and Savings.

Variables	Without other health insurance[19]	Without URRMI	Grouping using interview dates[20]
Household consumption	1207.242**	1222.449***	1223.152***
	(533.127)	(341.252)	(437.435)
Non-medical consumption	813.000**	787.898***	832.031**
	(355.498)	(301.793)	(337.244)
Food consumption	304.239***	354.574***	338.520***
	(114.297)	(103.869)	(111.005)
Saving	-1762.287***	-1950.985***	-1765.210***
	(544.139)	(483.523)	(526.503)
N	50011	49328	52521

Data source: 2011-2018 waves of CHARLS. *Notes:* The table reports the simple weighted average treatment effects of robustness check for consumption outcomes under conditional parallel trends assumption. The variables are taken per capita value. The estimates use the doubly robust estimator. ***, ** and * denote statistical significance at 0.01, 0.05, and 0.1 levels, respectively. Covariates: age, male, education level, marriage, family size, agricultural hukou, nonagricultural hukou, unified hukou, per capita GDP and urbanization rate.

test reported in Table 3.5, we find an increase but insignificant in any household consumption, non-medical consumption and food consumption, and a decrease but insignificant in any saving following the adoption of CII. We find a larger coefficient for household consumption in the placebo test, but it is not significant at all. The coefficient is smaller but significant in the main results. This may be due to the small sample size of the placebo test. Therefore, we find no evidence of a significant change in household consumption, non-medical consumption, food consumption or savings for the placebo sample, indicating that our main estimates are not driven by unobserved policies or shocks.

[19] Other medical insurance such as public health care, employee health insurance, or commercial health insurance.
[20] "Grouping using interview dates" is a grouping obtained using the year and month in which the respondents were interviewed matched to the time of CII implementation.

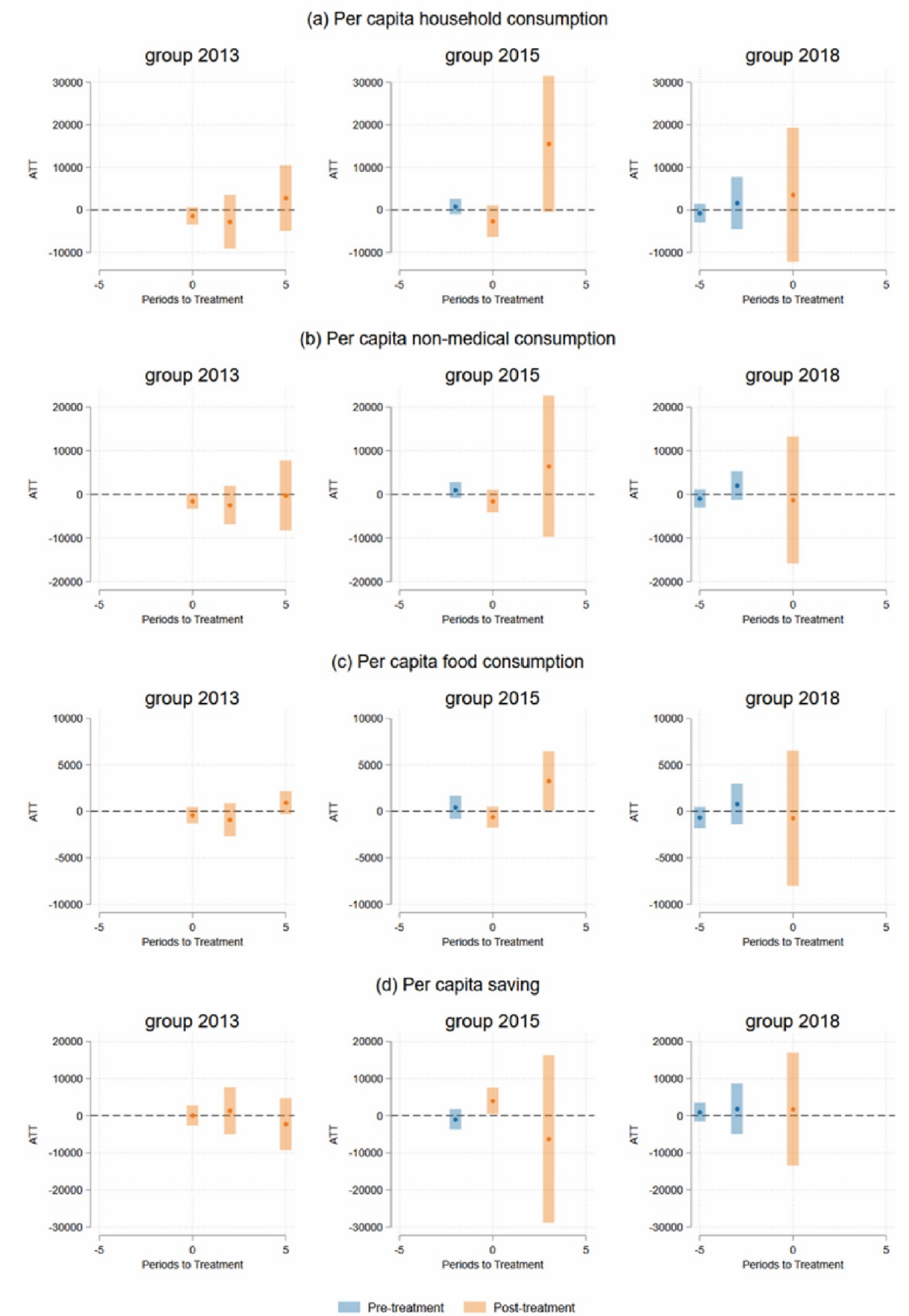

Figure 3.2. CII Event-study Average Treatment Effects on Consumption and Savings of Placebo Test.

Notes: The effect of the CII on per capita household consumption is Panel (a), per capita non-medical consumption is Panel (b), per capita medical expenditure is Panel (c), per capita food consumption is Panel (d), per capita non-food consumption is Panel (e), and per capita saving is Panel (f).

Table 3.5. Placebo Test on Consumption and Savings.

Variables	Simple weighted average	Pre-trend p-value
Household consumption	3440.956 (2120.281)	0.751
Non-medical consumption	533.362 (1863.892)	0.280
Food consumption	561.285 (436.218)	0.613
Saving	-437.436 (3003.307)	0.778
N	11233	

Data source: 2011-2018 waves of CHARLS. *Notes:* The table reports the simple weighted average treatment effects and p-value of the pre-trend of placebo test for health outcomes. The variables are taken per capita value. The estimates use the doubly robust estimator. ***, ** and * denote statistical significance at 0.01, 0.05, and 0.1 levels, respectively. Covariates: age, male, education level, marriage, family size, agricultural hukou, nonagricultural hukou, unified hukou, per capita GDP and urbanization rate.

Conclusion

Increasing consumption is essential for China's economic growth. As their physical functions decrease, middle-aged and older households are more susceptible to disease shocks than other age groups. According to the theory of precautionary savings, middle-aged and older households will preserve their current surplus income for the risk of uncertain future medical expenses. Using the DiD approach with doubly robust estimator, this study evaluates the effects of CII on consumption and saving outcomes of middle-aged and older households. We find that the adoption of CII significantly increases household per capita consumption by CNY 1,278.098, with non-medical consumption increasing by CNY 873.649 and food consumption increasing by CNY 438.504 and decreases per capita saving by CNY 1,752.614. Second, the analysis of heterogeneity demonstrates that the adoption of CII has a greater impact on rural households' consumption and saving than on urban households with middle-aged and older adults. In terms of age grouping, the CII program has a significant effect on total per capita consumption, food consumption and saving among individuals aged 60 and older. The CII program is found to effectively increase the non-medical consumption and reduce saving of middle-income households, taking into account the household economic situation. Based on the URMI and NCMS, the CII policy provides additional protection and defuses health concerns, which considerably encourages consumption among middle-aged and older households.

CHAPTER FOUR:

CONCLUSION

China's provinces and municipalities have gradually implemented a Critical Illness Insurance (CII) system based on URMI and NCMS since 2012. Using the doubly-robust Difference-in-Differences (DiD) estimator with multiple time periods proposed by Callaway and Sant'Anna (2020), this dissertation examines the impact of the full implementation of CII on health service utilization, health outcomes, household consumption, and savings of middle-aged and older adults residents using 2011, 2013, 2015, and 2018 four waves of micro household survey data from CHARLS. The results of the study are as follows:

First, we find that CII program significantly reduced out-of-pocket inpatient expenditures CNY 295.199 for middle-aged and older adults, and the effect of the CII program on inpatient OOP expenditures becomes stronger with greater exposure to the program. This indicates that the CII has a positive effect on reducing the burden of medical expenses for middle-aged and older adults through the price compensation mechanism. However, the introduction of CII reduces out-of-pocket spending significantly for middle-aged and middle-income populations but has a limited effect on older age groups over 60 and low-income populations, who face the greatest health risks and financial burdens. In addition, we do not find any statistically significant changes in total inpatient expenditures and in either the extensive or intensive margin of inpatient care. This suggests that the effect of the release of demand for medical services is not enough.

Utilization of inpatient services did not change immediately in response to the CII, but we do find a decrease in inpatient visits five years after implementation. The decrease in utilization could potentially reflect a reduction in medically unnecessary care or an improvement in health outcomes.

Second, we find that the CII adoption increases the probability of reporting “good” or “very good” health by 4 percentage points, conditional on covariates and results in a 12.7 percentage point reduction in ADL limitations. The rural residents, older adults, and low- and middle-income groups benefited the most from the health improvement impacts of the intervention. This indicates that the impact of CII on health improvement is effective for disadvantaged groups.

Furthermore, the implementation of CII promotes household consumption and reduce savings. Specifically, the adoption of CII significantly increases household per capita consumption by CNY 1278.098, with non-medical consumption increasing by CNY 873.649 and food consumption increasing by CNY 438.504 and decreases per capita saving by CNY 1752.614. For the response of different groups of households to the CII policy, rural residents and the older are the largest beneficiary groups, while the benefits to urban residents, middle-aged people and low-income groups are limited.

CII further provides supplementary protection and defuses health risks on top of basic medical insurance, significantly reducing residents' out-of-pocket expenses, leading to healthier residents, promoting household consumption, and reducing savings. However, since CII is still in the exploratory stage, its impact effect on residents, especially the vulnerable groups, has not yet been completely realized, and its system design and coverage content still need further improvement. To this regard, this study makes the following recommendations.

First, in terms of system design, differentiated compensation policies should be considered in the future to favor the poor and the older and improve the fairness of benefits. The difference in the threshold payment for different income levels and age groups should be taken into account when determining the standard threshold payment, so that disadvantaged groups can become the largest beneficiaries and the CII system can fully play its role in addressing "poverty caused by illness".

Moreover, improving the financing mechanism and raising the scale of financing for major medical insurance. The financing of major medical insurance is established by directly allocating a certain percentage of funds from NCMS and URMI funds, which does not increase the insureds' financial burden, but limits the fund size, thus affecting the level of protection. An insufficient fund size will directly affect the level of CII coverage and its effect on consumption promotion. Therefore, the financing system of CII can increase the funding methods of individuals, communities, and government subsidies to further increase the fund scale of CII.

Besides, innovating management mechanism to realize the provincial coordination of the CII. At the early stage of the pilot project, most regions adopted the management system of UMRI and NCMS for the CII, that is, fund balance within the prefecture-level municipalities. However, municipal-level coordination also limited the size of the CII fund, leading to differences in fund status and system design between regions, which resulted in different treatment levels. Therefore, the management system of basic medical insurance and CII should be further optimized in the future, gradually breaking down the barriers of municipal coordination, and exploring the implementation of provincial coordination under the premise of reasonable division of responsibilities between provincial and municipal governments. This can, on the one hand, realize mutual assistance and co-funding within the provincial area of the CII fund, and on the other hand, balance the system differences and treatment imbalance between regions.

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APPENDIX A: SUPPLEMENTARY TABLES

Table1. Time of CII Implementation for Sample Cities.

Province	City	Implementation Date	Resources and Link	Group
Anhui	Haozhou	2014	People’s Welfare Projects of Bozhou	2015
	Lu’an	Jan. 2013	The People's Government of Lu'an Municipality	2013
	Anqing	2014	Anqing Municipal People's Government	2015
	Suzhou	2014	Suzhou Municipal People's Government Suzhou Municipal People's Government	2015
	Chaohu	2013	Chaohu Municipal People's Government	2013
	Huainan	2014	The People's Government of Huainan Municipality	2015
	Fuyang	2014	Fuyang Municipal Human Resources and Social Security Bureau	2015
Beijing	Beijing	Jan. 2014	Beijing Municipal Commission of Development Reform	2015
Chongqing	Chongqing	Dec. 2013	Chongqing Municipal People's Government	2015
Fujian	Ningde	2016	Ningde Municipal People's Government	2018
	Zhangzhou	Jan. 2013	The People's Government of Zhangzhou Municipality	2013
	Fuzhou	Jan. 2013	Fuzhou Municipal People’s Government	2013
	Putian	2016	Putian Municipal People’s Government	2018
Gansu	Lanzhou	2017	Lanzhou Municipal People’s Government	2018
	Dingxi	2013	Dingxi Municipal People’s Government	2013
	Pingliang	Mar. 2015	Pingliang Municipal People’s Government	2015
	Zhangye	Apr. 2015	Pingliang Municipal People’s Government	2015
Guangdong	Foshan	Jul. 2013	Foshan Municipal People’s Government	2013
	Guangzhou	Sep. 2014	The People’s Government of Guangzhou Municipality	2015
	Jiangmen	Jan. 2016	Social Insurance Fund Administration of Jiangmen Municipality	2018
	Shenzhen	2014	The People’s Government of Shenzhen Municipality	2015
	Qingyuan	2013	The People’s Government of Qingyuan Municipality	2013
	Chaozhou	2013	The People’s Government of Chaozhou Municipality	2013

	Maoming	Jun. 2014	The People’s Government of Maoming Municipality	2015
Guangxi	Guilin	Dec. 2015	The People’s Government of Guilin Municipality	2018
	Nanning	2014	The People’s Government of Nanning Municipality	2015
	Hechi	Apr. 2015	The People’s Government of Hechi Municipality	2015
	Yulin	2017	The People’s Government of Yulin Municipality	2018
Guizhou	Qiandongnan Miao and Dong Autonomous Prefecture	2016	The People’s Government of Qiandongnan	2018
	Qiannan Buyi and Miao Autonomous Prefecture	2016	The People’s Government of Qiannan	2018
Henan	Xinyang	2015	The People’s Government of Xinyang Municipality	2015
	Zhoukou	Jan. 2015	The People’s Government of Zhoukou Municipality	2015
	Anyang	2014	The People’s Government of Henan Province	2015
	Pingdingshan	2014	The People’s Government of Henan Province	2015
	Luoyang	2014	The People’s Government of Henan Province	2015
	Puyang	2014	The People’s Government of Henan Province	2015
	Jiaozuo	2014	The People’s Government of Henan Province	2015
	Zhengzhou	Jul. 2013	The People’s Government of Henan Province	2013
Hebei	Baoding	2014	Baoding Municipal People's Government Baoding Municipal People's Government	2015
	Chengde	Jul. 2014	Chengde Municipal People's Government	2015
	Cangzhou	Sep. 2014	Office of the People's Government of Cangzhou City	2015
	Shijiazhuang	Mar. 2013	Shijiazhuang Municipal People's Government	2013
Heilongjiang	Jiamusi	Dec. 2015	The People’s Government of Jiamusi Municipality	2018
	Harbin	Aug. 2015	The People's Government of Harbin Municipality	2018
	Harbin city	Aug. 2015	The People's Government of Harbin Municipality	2018
	Jixi	2016	Heilongjiang Province People's Government	2018
	Qiqihar	Dec. 2015	The People’s Government of Qiqihar Municipality	2018

Hunan	Loudi	2016	The People's Government of Loudi Municipality	2018
	Yueyang	2016	The People's Government of Yueyang Municipality	2018
	Changde	Dec. 2013	The People's Government of Changde Municipality	2015
	Yiyang	Dec. 2014	The People's Government of Yiyang Municipality	2015
	Shaoyang	Dec. 2015	The People's Government of Shaoyang Municipality	2018
	Changsha	Dec. 2015	The People's Government of Shangsha Municipality	2018
Hubei	Enshi Tujia and Miao Autonomous Prefecture	2014	The People's Government of Hubei Province	2015
	Jingmen	2014	The People's Government of Hubei Province	2015
	Xiangyang	Sep. 2013	The People's Government of Xiangyang Municipality	2015
	Huanggang	Apr. 2013	The People's Government of Hubei Province	2013
Inner Mongolia	Hinggan League	Dec. 2015	People's Government of Inner Mongolia Autonomous Region	2018
	Hulunbeier	Dec. 2018	People's Government of Inner Mongolia Autonomous Region	0
	Hohhot	Dec. 2015	People's Government of Inner Mongolia Autonomous Region	2018
	Chifeng	Dec. 2015	People's Government of Inner Mongolia Autonomous Region	2018
	Xilingol League	Dec. 2015	People's Government of Inner Mongolia Autonomous Region	2018
Jiangsu	Suqian	Oct. 2013	The People's Government of Suqian Municipality	2015
	Xuzhou	Dec. 2013	The People's Government of Xuzhou Municipality	2015
	Yangzhou	Jan. 2014	The People's Government of Yangzhou Municipality	2015
	Taaizhou	2016	The People's Government of Jiangsu Province	2018
	Yancheng	Dec. 2013	The People's Government of Yancheng Municipality	2015
	Suzhou	Apr. 2018	The People's Government of Jiangsu Province	2018
	Lianyungang	Sep. 2015	The People's Government of Jiangsu Province	2018
Jiangxi	Shangrao	2014	The People's Government of Shangrao Municipality	2015
	Jiujiang	2014	The People's Government of Jiujiang Municipality	2015
	Nanchang	Sep. 2014	The People's Government of Jiangxi Province	2015

	Ji'an	2014	The People's Government of Jian Municipality	2015
	Yichun	2015	The People's Government of Yichun Municipality	2015
	Jingdezhen	2014	The People's Government of Jingdezhen Municipality	2015
	Ganzhou	2015	The People's Government of Ganzhou Municipality	2018
Jilin	Jilin	2014	The People's Government of Jilin Province	2015
	Siping	2014	The People's Government of Jilin Province	2015
Liaoning	Dalian	2013	The People's Government of Liaoning Province	2013
	Chaoyang	2013	The People's Government of Liaoning Province	2013
	Benxi	Jan. 2014	Benxi Municipal People's Government	2015
	Jinzhou	2013	The People's Government of Liaoning Province	2013
	Anshan	2013	The People's Government of Liaoning Province	2013
Qinghai	Haidong	2013	China Government Website	2013
Shandong	Linyi	2013	The People's Government of Shandong Province	2013
	Weihai	2014	The People's Government of Weihai Municipality	2015
	Dezhou	2014	The People's Government of Dezhou Municipality	2015
	Zaozhuang	2014	The People's Government of Zaozhuang Municipality	2015
	Jinan	Feb. 2013	The People's Government of Jinan Municipality	2013
	Binzhou	2014	The People's Government of Binzhou Municipality	2015
	Weifang	Mar. 2013	The People's Government of Weifang Municipality	2013
	Liaocheng	2013	The People's Government of Liaocheng Municipality	2013
	Qingdao	2013	The People's Government of Qingdao Municipality	2013
Shanghai	Shanghai	Jun. 2014	Shanghai Municipal Development & Reform Commission	2015
Shaanxi	Baoji	May. 2013	The People's Government of Baoji Municipality	2013
	Yulin	2017	The People's Government of Shaanxi Province	2018
	Hanzhong	May. 2013	The People's Government of Shaanxi Province	2013
	Weinan	2014	The People's Government of Weinan Municipality	2015
Shanxi	Linfen	2015	The People's Government of Shanxi Province	2015

	Xinzhou	2015	The People’s Government of Shanxi Province	2015
	Yuncheng	Sep. 2013	The People’s Government of Shanxi Province	2015
	Yangquan	May. 2013	Yangquan Municipal People's Government	2013
Sichuan	Neijiang	Dec. 2014	The People’s Government of Neijiang Municipality	2015
	Liangshan Yi Autonomous Prefecture	2014	The People’s Government of Liangshan Yi Autonomous Prefecture	2015
	Nanchong	Jan. 2013	The People’s Government of Sichuan Province	2013
	Yibin	2014	The People’s Government of Sichuan Province	2015
	Guang'an	Apr. 2015	The People’s Government of Guangan Municipality	2015
	Chengdu	2014	The People's Government of Sichuan Province	2015
	Tibetan Autonomous Prefecture of Garzê	2014	The People’s Government of Sichuan Province	2015
	Meishan	2014	The People’s Government of Meishan Municipality	2015
	Mianyang	Jan. 2015	The People’s Government of Sichuan Province	2015
	Ziyang	2014	The People’s Government of Ziyang Municipality	2015
Tianjin	Tianjin	July. 2014	Tianjin Municipal Human Resources and Social Security Bureau	2015
Xinjiang	Aksu	2019	The People’s Government of Aksu Municipality	0
Yunnan	Lincang	2018	The People’s Government of Lincang Municipality	0
	Lijiang	2017	The People’s Government of Lijiang Municipality	2018
	Baoshan	2016	The People’s Government of Baoshan Municipality	2018
	Kunming	Jan. 2013	The People’s Government of Kunming Municipality	2013
	Zhaotong	Jun. 2014	The People’s Government of Zhaotong Municipality	2015
	Chuxiong	Dec. 2015	The People's Government of Chuxiong Yi Autonomous Prefecture	2018
Zhejiang	Lishui	2015	The People's Government of Lishui Municipality	2015
	Taizhou	2015	The People's Government of Taizhou Municipality	2015
	Jiaxing	2014	The People's Government of Jiaxing Municipality	2015

	Ningbo	2014	The People's Government of Ningbo Municipality	2015
	Hangzhou	Dec. 2015	The People's Government of Hangzhou Municipality	2018
	Huzhou	Feb. 2013	The People's Government of Huzhou Municipality	2013

Notes: The implementation dates of CII policies for each prefecture city were compiled by consulting websites. Group 2013 refers to cities that began implementing the policy before July 2013. Group 2015 refers to cities that began implementing the policy from August 2013 to July 2015. Group 2018 refers to cities that began implementing the policy from August 2015 to July 2018.

Table 2. Definition of Variables.

Variables name	Definition
Medical expenditures	
Inpatient OOP expenditures	Inpatient OOP expenditures in the past year
Total inpatient expenditures	Total inpatient expenditures in the past year
Healthcare utilization	
Whether hospitalized	= 1 if having received inpatient care in the past year, = 0 if not
Number of hospitalizations	Respondent's number of hospitalizations in the past year
Age	Respondent's age
Male	=1 if male, =0 if female
Education	
No formal education	=1 if no formal education (illiterate), = 0 otherwise
Incomplete primary education	= 1 if did not finish primary school but capable of reading or writing, = 0 otherwise
Elementary school	= 1 if highest education level is elementary school, = 0 otherwise
Middle school	= 1 if highest education level is middle school, = 0 otherwise
High school and above	= 1 if highest education level is or above high school, = 0 otherwise
Marriage	=1 with spouse (married and living with spouse and not living with spouse), =0 no spouse (divorced, widowed, never married)
Number of family members	The number of persons living in this household
Agricultural hukou	=1 if have agricultural hukou, =0 otherwise
Non-agricultural hukou	=1 if have non-agricultural hukou, =0 otherwise
Unified residence hukou	=1 if have unified residence hukou, =0 otherwise

Table 3. Group-time Average Treatment Effects on Inpatient OOP Expenditures.

	Unconditional parallel trends	Conditional parallel trends
Group 2013		
t 2011-2013	-47.844	-78.854
	(92.650)	(100.706)
t 2011-2015	-276.151**	-247.221
	(140.342)	(152.033)
t 2011-2018	-629.691**	-851.304***
	(261.868)	(289.558)
Group 2015		
t 2011-2013	99.785	124.323
	(106.499)	(109.526)
t 2013-2015	-231.300*	-206.430*
	(131.297)	(125.402)
t 2013-2018	-658.930***	-214.415
	(146.589)	(289.498)
Group 2018		
t 2011-2013	-76.639	-63.365
	(112.667)	(122.992)
t 2013-2015	84.032	304.101
	(196.647)	(247.787)
t 2015-2018	-479.602***	-434.313**
	(179.509)	(217.248)

Notes: Group-time average effects are reported for doubly-robust DiD estimator under unconditional parallel trends and conditional parallel trends respectively. Clustered standard errors at the prefecture city level are in parentheses. ***, ** and * denote statistical significance at 0.01, 0.05, and 0.1 levels, respectively.

Table 4. Group-time Average Treatment Effects on Total Inpatient Expenditures.

	Unconditional parallel trends	Conditional parallel trends
Group 2013		
t 2011-2013	-84.519	-99.774
	(141.952)	(153.619)
t 2011-2015	-19.674	17.471
	(219.237)	(238.211)
t 2011-2018	-445.624	-113.969
	(427.882)	(265.653)
Group 2015		
t 2011-2013	-17.372	14.971
	(175.257)	(172.312)
t 2013-2015	-43.360	0.474
	(185.028)	(175.685)
t 2013-2018	-438.274	331.910
	(364.298)	(473.719)
Group 2018		
t 2011-2013	61.757	87.829
	(186.822)	(193.183)
t 2013-2015	22.889	400.981
	(254.525)	(389.019)
t 2015-2018	-269.084	-215.293
	(289.176)	(318.840)

Notes: Group-time average treatment effects are reported for doubly-robust DiD estimator under unconditional parallel trends and conditional parallel trends respectively. Clustered standard errors at the prefecture city level are in parentheses. ***, ** and * denote statistical significance at 0.01, 0.05, and 0.1 levels, respectively.

Table 5. Group-time Average Treatment Effects on Health Care Use.

	Whether hospitalized	Number of hospitalizations
Group 2013		
t 2011-2013	-0.000	-0.001
	(0.010)	(0.020)
t 2011-2015	-0.006	-0.005
	(0.016)	(0.025)
t 2011-2018	-0.067*	-0.093**
	(0.038)	(0.047)
Group 2015		
t 2011-2013	0.000	-0.025
	(0.015)	(0.028)
t 2013-2015	0.007	0.025
	(0.012)	(0.023)
t 2013-2018	0.049	0.136**
	(0.035)	(0.064)
Group 2018		
t 2011-2013	0.003	0.032
	(0.017)	(0.033)
t 2013-2015	-0.027	0.028
	(0.027)	(0.050)
t 2015-2018	0.059	0.048
	(0.046)	(0.070)

Notes: Group-time average treatment effects are reported for doubly-robust DiD estimator under unconditional parallel trends and conditional parallel trends respectively. Clustered standard errors at the prefecture city level are in parentheses. ***, ** and * denote statistical significance at 0.01, 0.05, and 0.1 levels, respectively.

Table 6. Group-time Average Treatment Effects on Health Care Use and Medical Expenditures of Placebo Test.

	Inpatient OOP expenditures	Total inpatient expenditures	Whether hospitalized	Number of hospitalizations
Group 2013				
t 2011-2013	-227.976	982.241	0.018	0.052
	(335.820)	(776.649)	(0.026)	(0.066)
t 2011-2015	-461.473	643.479	0.011	0.066
	(379.638)	(585.109)	(0.036)	(0.066)
t 2011-2018	-145.137	-1271.025	-0.096	0.031
	(1881.106)	(4370.495)	(0.123)	(0.149)
Group 2015				
t 2011-2013	-161.569	-223.290	0.024	0.075*
	(300.690)	(546.802)	(0.025)	(0.044)
t 2013-2015	-77.547	767.059	-0.042	-0.040
	(375.929)	(704.098)	(0.028)	(0.052)
t 2013-2018	-480.091	680.388	0.007	0.144
	(455.096)	(1558.767)	(0.107)	(0.274)
Group 2018				
t 2011-2013	99.955	-12.903	-0.024	-0.068*
	(333.865)	(471.965)	(0.020)	(0.040)
t 2013-2015	-744.267	-324.510	0.095	0.139
	(513.018)	(873.467)	(0.062)	(0.211)
t 2015-2018	3595.284***	4171.603*	0.210***	0.368**
	(893.606)	(2260.484)	(0.077)	(0.161)

Notes: Group-time average effects are reported for doubly-robust DiD estimator with multiple time periods. Clustered standard errors at the prefecture city level are in parentheses. ***, ** and * denote statistical significance at 0.01, 0.05, and 0.1 levels, respectively.

Table 7. Group-time Average Treatment Effects on Health Outcomes.

	Good	Fair	Poor	Health index	ADL limitations
Group 2013					
t 2011-2013	-0.002	0.022	-0.019	-0.012	-0.016
	(0.014)	(0.020)	(0.017)	(0.014)	(0.049)
t 2011-2015	-0.024	0.033	-0.008	-0.011	-0.108*
	(0.019)	(0.026)	(0.021)	(0.015)	(0.058)
t 2011-2018	0.051**	0.047	-0.098*	-0.227***	-0.464***
	(0.024)	(0.048)	(0.056)	(0.066)	(0.072)
Group 2015					
t 2011-2013	0.002	0.008	-0.010	0.009	-0.071
	(0.016)	(0.022)	(0.017)	(0.012)	(0.050)
t 2013-2015	-0.024*	0.022	0.002	-0.005	-0.041
	(0.014)	(0.019)	(0.014)	(0.010)	(0.040)
t 2013-2018	0.143***	-0.096***	-0.046	-0.019	-0.138***
	(0.034)	(0.034)	(0.041)	(0.080)	(0.033)
Group 2018					
t 2011-2013	-0.018	0.006	0.012	-0.019	0.027
	(0.018)	(0.023)	(0.017)	(0.011)	(0.053)
t 2013-2015	0.054	-0.011	-0.043	-0.009	-0.062
	(0.035)	(0.040)	(0.058)	(0.050)	(0.055)
t 2015-2018	0.102***	-0.028	-0.074	-0.027	-0.110**
	(0.032)	(0.055)	(0.054)	(0.041)	(0.054)

Notes: Group-time average effects are reported for doubly-robust DiD estimator with multiple time periods. Clustered standard errors at the prefecture city level are in parentheses. ***, ** and * denote statistical significance at 0.01, 0.05, and 0.1 levels, respectively.

Table 8. Group-time Average Treatment Effects on Health Outcomes of Placebo Test.

	Good	Fair	Poor	Health index	ADL limitations
Group 2013					
t 2011-2013	0.006	0.008	-0.014	0.020	0.028
	(0.028)	(0.029)	(0.025)	(0.024)	(0.059)
t 2011-2015	0.065	-0.050	-0.015	0.051	-0.024
	(0.051)	(0.051)	(0.029)	(0.047)	(0.098)
t 2011-2018	-0.098	0.402**	-0.304***	-0.103	-0.141
	(0.089)	(0.170)	(0.109)	(0.164)	(0.101)
Group 2015					
t 2011-2013	0.012	-0.029	0.017	0.047*	0.028
	(0.030)	(0.039)	(0.026)	(0.025)	(0.091)
t 2013-2015	-0.058**	0.070**	-0.012	0.035	0.046
	(0.027)	(0.033)	(0.020)	(0.027)	(0.047)
t 2013-2018	-0.022	0.132	-0.110	-0.021	-0.128
	(0.119)	(0.165)	(0.109)	(0.089)	(0.195)
Group 2018					
t 2011-2013	-0.016	0.042	-0.026	-0.043*	-0.069
	(0.032)	(0.041)	(0.028)	(0.023)	(0.051)
t 2013-2015	-0.153*	0.061	0.092	0.071	-0.133
	(0.087)	(0.077)	(0.148)	(0.079)	(0.094)
t 2015-2018	-0.191	-0.178**	0.368**	0.167	-0.147
	(0.167)	(0.076)	(0.161)	(0.193)	(0.134)

Notes: Group-time average effects are reported for doubly-robust DiD estimator with multiple time periods. Clustered standard errors at the prefecture city level are in parentheses. ***, ** and * denote statistical significance at 0.01, 0.05, and 0.1 levels, respectively.

Table 9. Group-time Average Treatment Effects on Consumption and Savings.

	Total household consumption	Non-medical consumption	Food consumption	Saving
Group 2013				
t 2011-2013	-471.647	-446.436*	-124.466	560.011
	(310.550)	(247.792)	(131.300)	(454.241)
t 2011-2015	263.438	140.280	27.491	1137.437
	(741.111)	(638.811)	(210.855)	(789.199)
t 2011-2018	-669.119	-737.060	300.467	-3057.016*
	(689.830)	(741.914)	(279.700)	(1627.122)
Group 2015				
t 2011-2013	-363.971	-298.292	-200.964	986.357*
	(459.953)	(376.316)	(167.922)	(549.189)
t 2013-2015	495.070	152.589	155.436	-451.308
	(455.048)	(395.442)	(150.377)	(377.915)
t 2013-2018	3902.897***	3144.606***	1243.766***	-5388.427***
	(1121.583)	(703.152)	(263.586)	(1148.684)
Group 2018				
t 2011-2013	130.687	218.717	95.288	-667.721
	(524.478)	(425.386)	(177.702)	(590.649)
t 2013-2015	48.034	-726.372	-443.423	909.060
	(2787.626)	(758.986)	(456.298)	(1523.182)
t 2015-2018	2959.672**	1823.065*	504.719	-524.846
	(1343.722)	(1075.516)	(477.668)	(2667.293)

Notes: Group-time average effects are reported for doubly-robust DiD estimator with multiple time periods. Clustered standard errors at the prefecture city level are in parentheses. ***, ** and * denote statistical significance at 0.01, 0.05, and 0.1 levels, respectively.

Table 10. Group-time Average Treatment Effects on Consumption and Savings of Placebo Test.

	Total household consumption	Non-medical consumption	Food consumption	Saving
Group 2013				
t 2011-2013	-1410.841	-1535.414*	-404.412	85.127
	(1019.114)	(867.932)	(454.613)	(1378.787)
t 2011-2015	-2781.310	-2451.075	-899.642	1355.257
	(3196.998)	(2246.704)	(912.065)	(3243.600)
t 2011-2018	2803.857	-34.499	947.439	-2243.126
	(3934.637)	(4088.222)	(633.114)	(3569.990)
Group 2015				
t 2011-2013	790.760	992.522	432.190	-984.458
	(919.802)	(915.320)	(643.746)	(1405.633)
t 2013-2015	-2646.645	-1548.519	-608.487	4026.758**
	(1890.066)	(1326.358)	(570.598)	(1802.042)
t 2013-2018	15833.278*	6783.407	3290.280**	-6373.212
	(8160.272)	(8260.063)	(1622.551)	(11522.266)
Group 2018				
t 2011-2013	-730.047	-957.739	-666.143	965.267
	(1114.853)	(1058.741)	(588.095)	(1289.275)
t 2013-2015	1628.826	2030.431	796.597	1874.221
	(3139.471)	(1673.730)	(1116.470)	(3487.821)
t 2015-2018	3556.667	-1304.960	-729.688	1777.752
	(8020.817)	(7417.261)	(3711.689)	(7766.925)

Notes: Group-time average effects are reported for doubly-robust DiD estimator with multiple time periods. Clustered standard errors at the prefecture city level are in parentheses. ***, ** and * denote statistical significance at 0.01, 0.05, and 0.1 levels, respectively.