

# Public Health Insurance Reform and the Demand for Medical Care in China

Xi Wang<sup>\*†</sup>

This version: December 2021

## Abstract

In 2016, there was a major Chinese health insurance reform that integrated non-working urban residents' and rural residents' health insurance plans, which were treated differently before the reform, aiming to provide a lower co-insurance rate. This paper estimates the impact of this integration of health insurance plans on the Chinese elder's health care utilization and medical spending. Three different identification strategies are adopted: probit model, DD with continuous treatment, and DD with different treatment timings. The reform significantly increased the elder inpatient health care utilization by 16 ~ 37% but had no significant effect on outpatient health care utilization. This is caused by the reimbursement process in the public health insurance system and the cheap medical services for outpatients in China. I also find no significant changes in out-of-pocket medical spending after the reform or narrowed rural-urban disparity in healthcare utilization.

*JEL classification:* H42, I38, L33, L44, L66.

*Keywords:* Health insurance reform; outpatient health care; inpatient health care.

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\*The University of Georgia, John Munro Godfrey, Sr. Department of Economics, Email: [xwang975@uga.edu](mailto:xwang975@uga.edu)

†I am deeply indebted to Eli Liebman for numerous stimulating conversations and insightful suggestions. My gratitude extends to Mateusz Filipski for his continuing encouragement and support, and to Matt Knepper for his invaluable suggestions. All errors are my own.

# 1 Introduction

The public health insurance system plays an important role in developing countries for two reasons. First, the public health insurance system as a welfare program requires a large amount of government spending. Secondly, the imbalance between the increasing price of medical services and the relatively lower income growth rate caused many non-working citizens or residents from rural areas to be unable to afford medical spending, then decreasing their health care utilization.

To expand the public health insurance coverage and improve social welfare, China initiates several rounds of health insurance reforms in the past 20 years. The integrated health insurance reform (IHI), as the most significant overhaul, aims to a) decrease the coinsurance rate of public health insurance; and b) narrow the disparity in medical spending between urban and rural residents.

This paper evaluates the IHI reform from three aspects. First, I investigate how this reform influences people's out-of-pocket medical spending by estimating a two-way fixed-effect model. Secondly, I study whether this reform increases enrollees' healthcare utilization by using the probit model. Thirdly, I study whether this reform alleviates the disparity in out-of-pocket medical expenditures between rural residents and urban residents.

I estimate the model by using CHARLS data sources and merge 4 waves data as a balanced panel with 10,341 observations from 2011 to 2017. According to my sample, there are 46 cities that implemented the reform in the year 2011, 36 cities implemented in 2013, 26 cities implemented the reform in 2015, 12 cities implemented in 2017, and the rest 5 cities had not reformed in the last wave. Using the detailed information on the city that one lives in, I can construct a dummy variable to indicate when each observation received the treatment. Besides, the dummy variable that indicates whether a person lives in rural areas helps me identify the heterogeneous treatment effects between rural and urban residents in China.

The summary statistics show that inpatient and outpatient health care are stable in the treatment and control groups before and after the reform. There are no significant changes in self-paid medical spending in reformed and non-reformed cities before and after the reform, and the details are shown in section 3.

First, I estimate the two-way fixed effect model and find that the reform decreases inpatient out-of-pocket medical expenditure by 5 dollars and increases outpatient self-paid expenditure by 4 dollars. However, the cost data has a left-skewness problem, so I estimate a two-part model to solve it. The new result shows that the reform increases

Chinese elders' out-of-pocket medical spending after controlling for the inflation, but there are no statistically significant results.

Second, I use the probit model without individual fixed effects to study the impact of the reform on healthcare utilization. The results show that the reform significantly increases the chance of receiving outpatient healthcare by 25.6% after controlling the elder's demographic characteristics and health status. However, there are no significant changes in outpatient health care utilization.

Third, I estimate a two-way fixed effect model and find no significant results on narrowing the rural-urban disparity in health care utilization. Nonetheless, the reform did increase the probability that urban residents receive inpatient healthcare by 15.4%, and increase that for rural residents by 26%.

Lastly, considering that the treatment effects are heterogeneous across cities, I use DD with different treatment timings (Callaway and Sant'Anna, 2020) to study the impact of the reform. The group-specific average treatment results show that the reform led to the following changes: a) group 2013 has a lower probability of receiving outpatient healthcare utilization, which is around 5.84% ~ 16.67%, but a higher probability of receiving inpatient healthcare, which is around 11.56%, when compared with group 2015 and group 2017; b) group 2017 has the highest probability of receiving outpatient healthcare utilization, which is 8.89%, and a statistically significant lower probability of receiving inpatient healthcare, which is 20.06%.

These results are caused by the reimbursement process in the public health insurance system and the cheap medical services for outpatient. In China, the medical balance due to patients is the total medical expenditure, which is different from American medical billing that shows the final self-paid amount. Hence, even though a patient has enrolled in a health insurance plan, she must first pay the entire medical costs by herself. Then, she could take her medical bills and receipts to the local government to ask for the money return based on the coinsurance rate. Since the amount of medical cost for outpatient healthcare is usually low (e.g., less than \$10 for a clinic visit), most patients do not want to waste time on traveling to the local government to get a small amount of reimbursement, although they are facing a lower level of coinsurance rate after the reform. Therefore, the results that show an increasing amount of inpatient healthcare and no changes in outpatient are consistent with the theory.

The paper contributes to the existed literature that focuses on studying how health insurance reform impacts the Chinese demand for health care. However, the literature exhibits substantial disagreement. For example, Liu (2017), Wang et al. (2019) and Su et al. (2019) find that the integrated health insurance has no significant impact on allevi-

ating the disparities in health care utilization between the urban and rural areas, nor no significant effect on the health care utilization in rural areas. By contrast, Huang (2017) and Li et al. (2019) all obtain the opposite results, and they find that URRMI significantly increased the health care utilization in rural areas and narrowed the urban-rural disparity. This disagreement reflects that our understanding of the implication of integrated health insurance is still limited. Table 1 and table 2 show the disagreements of existed literature. Besides, relative to the extensive discussion about the health care utilization through each insurance channel, the issue about the impact of integrated health insurance on medical spending has received less attention. This paper aims at moving a step forward toward a solid understanding of this issue.

The rest of the paper is organized as follows. Section 2 describes the details of background information. Section 3 describes the data. Section 4 explains my estimation strategy. Section 5 shows the estimation results. Section 6 is robustness, and section 7 is conclusion. Additional details and tables are in the appendix.

Table 1: Overview of Existed Studies in the Evaluation of Integrated Health Insurance

No.	Paper	Data	Identification Strategy	Relation with my paper	Finding
1.	Liu (2017)	CHARLS (2011-2013)	PSM-DiD	Liu used canonical DiD method and treated 2014 as the year threshold, but I used TWFE method with different treatment timings to study the group-specific effects.	The integrated health insurance had no significant changes in disparities in health care utilization between urban and rural areas
2.	Mao et al. (2018)	Longitudinal survey data (2009-2013)	OLS	Mao studies the association between insurance enrollment decision and the enrollee's health status, but this paper evaluated the IHI reform.	The existence of adverse selection was shown, when people can choose to switch from previous plan to enroll in URRMI.
3. 4	Huang (2017)	Clinic data in Guangzhou, China (2014-2015)	DiD	Huang focused on studying the impact of IHI on Guangzhou, and this paper studies how the reform influences overall healthcare utilization	The integrated health insurance had significantly increased the health care utilization in the rural area and decreased 8.8% of the OOP for enrollees from rural areas.
4.	Zhu et al. (2017)	China Health Statistics Year Book (2008-2015)	Descriptive Study	Zhu focused on the supply-side, and this paper focus on the demand-side.	The scale of financing for URRMI is insufficient for the increasing demands for medical services from the insured.

Table 2: Overview of Existed Studies in the Evaluation of Integrated Health Insurance

No.	Paper	Data	Identification Strategy	Relation with my paper	Finding
5.	Su et al. (2019)	CHARLS (2011-2015)	PSM-DiD	1)I used CHARLS data from 2011-2017; 2) Our identification strategies are different	For rural populations, the URRMI policy has significantly reduced their outpatient care and significantly increased their OOP costs.
6.	Yang et al. (2018)	The 5th National Health Survey (2013)	OLS	Yang used the absolute amount of reimbursement received as the dependent variable, and I used medical spending and health care utilization as dependents.	Individuals received more inpatient care benefits when the health insurance were integrated.
7.	Wang et al. (2019)	CHARLS (2015)	Binary Logistic Regression	Wang evaluated the impact a different health insurance reform which is URBMI.	There is no statistically significant difference in healthcare utilization between URBMI and NRCMS.
8.57	Li et al. (2019)	CHARLS (2013-2015)	DiD	I used different identification strategies: probit model, DD with different treatment timings, DD with continuous treatments	The integration had no impact on narrowing the urban-rural disparities in health care utilization, but had significant and positive effects on the number of outpatient visits and inpatient visits for rural residents.

## 2 Background Information

This section introduces the basic features of the Chinese health insurance system before and after implementing the integrated health insurance reform.

Before the IHI reform, for the vast majority of households in China, health insurance was attainable via three different channels: new rural cooperative medical insurance (NRCMI), urban employee medical insurance (UEMI), and urban resident basic medical insurance (URBMI). There were two features of this old-version health insurance system.

The first feature was its tie to the labor market. UEMI, which was similar to the American employer-sponsored health insurance<sup>1</sup>, covered almost all urban employees who have labor contracts with their employers, except labor forces who work for the government<sup>2</sup>. By contrast, people who do not have labor contracts or live in rural areas, are not eligible for the UEMI, but could **voluntarily** participate in either NRCMI or URBMI, depending on their living location.

The second feature was its tie to the living location. URBMI was provided for the urban residents who do not work or do not have the labor contract, includes the older who are older 60<sup>3</sup>, the younger who are younger than 18, and the unemployed. NRCMI aimed to provide all rural residents health insurance, first implemented in 2003 and developed as the largest health insurance plan in China. The coinsurance rate of URBMI was overall lower than the NRCMI, which directly causes the disparity in medical spending between rural and urban residents. According to studies from Pan et al. (2016), Lei and Lin (2009) and Green et al. (2021), urban residents have a higher health care utilization than the rural residents.

To solve this rural-urban inequality of health care utilization, the Chinese government initiated the integrated health insurance reform (HIH) since 2011. The reform brought three changes:

First, the reform integrated the URBMI and NRCMI as one new medical insurance scheme, known as the "Urban and rural resident medical insurance" scheme (URRMI). Therefore, if a city experienced the reform, URBMI and NRCMI are no longer provided,

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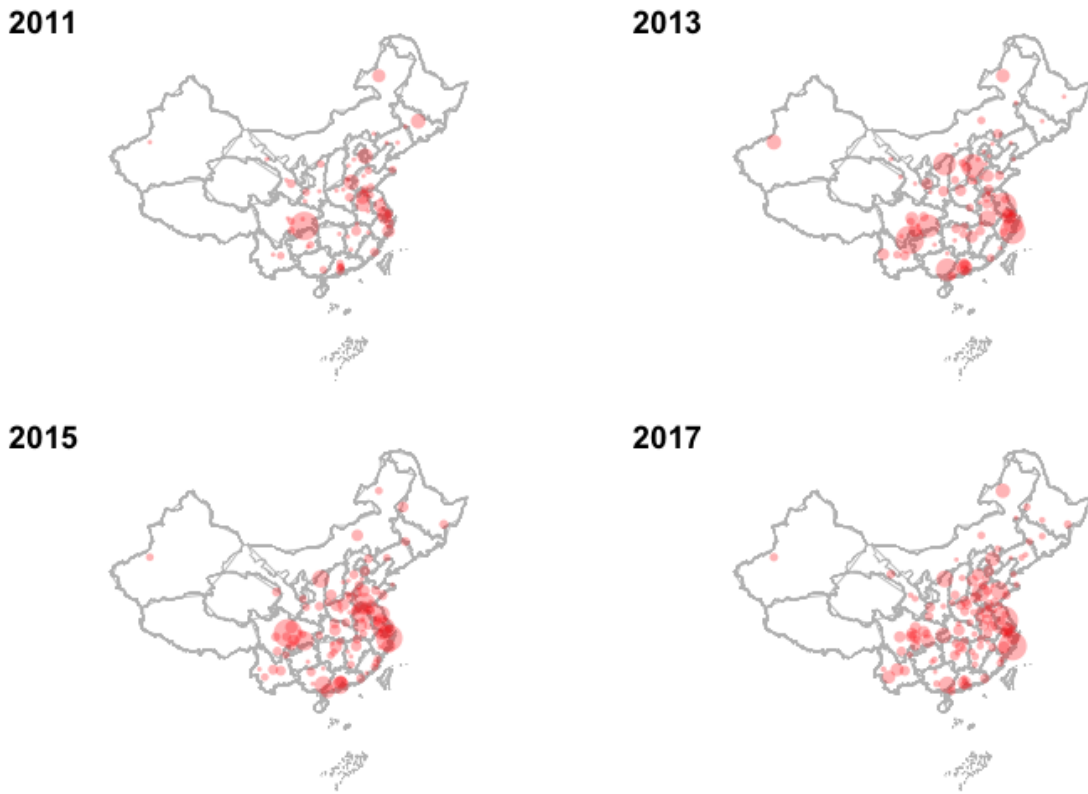
<sup>1</sup>Differs from American employer-sponsored health insurance, Chinese UEMI provides lifetime health insurance coverage for its enrollees, no matter whether the employee retires or not, but the reimbursement rate changes if one enrollee retires. Hence, UEMI can be understood as a combination of American employer-sponsored health insurance and Medicare. Although providing UEMI for all full-time workers is mandatory for Chinese employers, many private companies do not practice the policy in reality. As one can expect, providing lifetime UEMI for employees is a heavy burden for the company.

<sup>2</sup>People who work in government enrolled in Government Health Insurance, and they pay monthly premiums through their salaries and enjoy a one hundred percent reimbursement rate.

<sup>3</sup>The age threshold varies by city. Most cities chose 60 as the threshold because it is the official retirement age for Chinese male workers.

and only URRMI is provided for eligible rural and urban residents.<sup>4</sup> Since the integrated health insurance reform was implemented based on the city level, it turns out that some cities reformed earlier, and the other reformed later. It is worth knowing the geographic distribution of enrollees for URRMI by year. Figure 1 presents this distribution from 2011 to 2017, which suggests that the number of enrollees in each city is increasing, and the enrollees are widely distributed across the east, middle, and south of China.

Figure 1: Geographic Distribution of URRMI



Secondly, URRMI provides the same coinsurance rate to all eligible rural and urban residents, which was reflected on the same premium fees for all enrollees who live in the same geographic area, regardless of whether or not they live in the urban areas. However, the specific premium and coinsurance rates differ by cities, because of the existed disparity in living standards and development among cities. I provide examples to describe

<sup>4</sup>In my sample, some cities reported finishing the reform but had a positive number of enrollees for either NRCMI or URBMI after the reform. Through talking with the government's staff, I realized that the reform's implementation dates vary with the county in each city. For example, Baoshan city implemented the reform in 2013, and ideally, there should be 0 enrollees for NRCMI after the reform. However, the sample shows that 71 residents still enrolled in NRCMI in 2015. The reason behind this fact is that Baoshan city governed 10 counties, and two counties had not yet reformed in 2015, so 71 residents were from these two counties.



how cities implemented the reform in Appendix table and table <sup>5</sup>.

Lastly, the coinsurance rate **decreased** after the reform based on the requirement from State Council (State Council, 2016) <sup>6</sup>, and the decreasing amounts vary by city. Theoretically, the demands for medical care should increase after the reform since the actual price for medical care declined. Table 3 shows how coinsurance rate changes in Guangzhou city.

Table 3: Health Insurance Schemes in China: Guangzhou

Types	Before Integration		After Integration
	NRCMI	URBMI	URRMI
Start Year	2003	2007	2011-2016
Unit	Household	Household	Individual
Type	Voluntary	Voluntary	Voluntary
Coverage Residents	County (rural)	City (urban)	City,County,District (rural and urban)
In-Network Hospitals	Fewer choices	More choices	Same as URBMI
Coinsurance rate	40%	50%	40% ( <b>More Generous</b> )
Premium fees(RMB)	730	Age ≤ 18: 40 Age ≥ 70: 440 Unemployed: 230	152
Payment Method	Fee-for-service	Fee-for-service	Fee-for-service

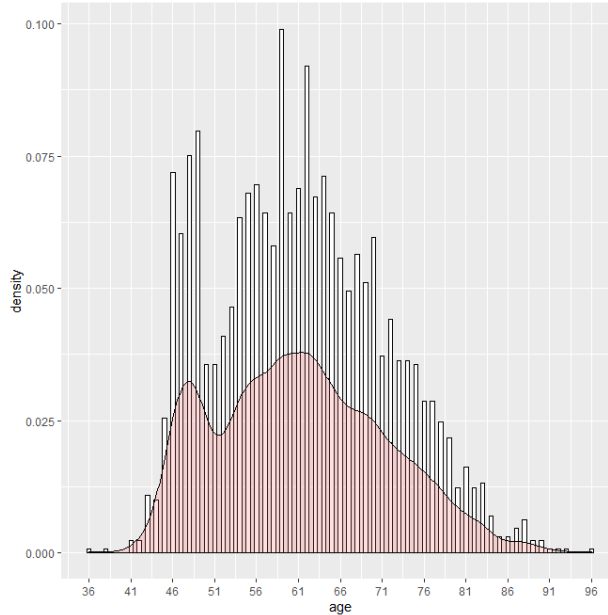
### 3 Data

I used Charls (Chinese Health and Retirement Longitudinal Study) data to evaluate IHI reform on residents' medical spending and health care utilization. The Charls data is a longitudinal survey data and its questionnaires referenced those in HRS(the Health and Retirement Survey), ELSA(the English Longitudinal Study of Aging), and SHARE(the Survey of Health, Aging, and Retirement in European), which aims to provide information on household's health insurance, medical spending, family income, inter-generation transfers, and health status. It was initially surveyed in 2011 and then was followed up every two years. Now it has four waves that cover a period between 2011 and 2017. The Charls data surveyed individuals older than 45 and these individuals' family members, so the data includes information for retirees, workers, and the unemployed. The baseline

<sup>5</sup>Although the table includes the Government health insurance (GHI), observations who work in local government occupy a small fraction of the sample. Therefore, I will not study this plan in this paper.

<sup>6</sup>[http://www.gov.cn/zhengce/content/2016-01/12/content\\_10582.htm](http://www.gov.cn/zhengce/content/2016-01/12/content_10582.htm)

Figure 2: Sample: Age distribution



survey was conducted in 125 cities among 28 provinces, 150 counties, 450 villages across the country. Hence, it is a representative sample of the non-institutional population in China.

### 3.1 Sample Selection

I narrowed the sample on people who are either non-working urban-residents or rural residents, because the reform aims to impact these two types of residents. In my sample, there are 2588 observations who appeared in all 4 waves datasets, which consists a balanced panel data. Figure 2 shows the age distribution for the sample, which implies that most individuals are aged from 46-76.

### 3.2 Summary Statistics

In this section, I summarize how outcomes vary across individuals. Table 4 (Panel A-D) summarizes the percentage of residents by their demographic information, health status, and family closeness, pre and post the reform for different reformed groups and non-reformed group. Panel A shows that the demographic distribution in each group is largely stable, except for the living locations. We could find that most treated individuals are from rural areas, and most individuals in the control group are from the urban areas. It also shows that residents in reformed groups tend to have higher chances to have the

bank loan than those in the control group. Panel B shows the mean and median values of family income by different groups. Considering the target group of this reform are either non-working urban residents or rural residents, I calculated their family non-housing financial wealth and used it to measure family income. There are no obvious differences between treatment groups and the control group. Since monetary transfers from children could be an important factor to influence Chinese elder's healthcare utilization, I also include it and the mean value of transfers are stable among groups, but control group has a higher median value for transfers than the treatment group. Panel C summarizes the percentage of residents by their health status, and the health distribution in each group is largely stable. Healthy is defined by self-reported health with very good, good and fair. However, the percentage of individuals who suffered chronic diseases, are higher in control group than that in other treatment groups. Panel D shows the distribution of family closeness by groups. In the sample, there are around 67% percentage of individuals have their children live nearby, and the table implies that treatment groups on average are more frequently contact with their children than control group does.

Table 5 (Panel A-D) summarizes individual-level statistics from the Charls, before and after the IHI reform and separately for IHI reformed cities and non-reformed cities. The number of nights for hospitalization has a slightly higher increasing in reformed cities than those in non-reformed cities. The changes in inpatient health care and outpatient health care are stable in the treatment group and the control group, before and after the reform. There are no significant changes in self-paid medical spending in reformed and non-reformed cities, before and after the reform.

Table 4: Individual Level Summary Statistics

Residents	Group 1	Group 2	Group 3	Group 4	Control
Sample Size:	959	755	549	181	144
<b>A. Demographics (%)</b>					
Urban	31.12	22.65	24.04	30.94	77.78
Male	41.89	46.38	44.99	45.30	41.67
Illiterate	43.98	44.74	45.58	40.75	43.75
Agricultural ID	54.29	54.37	56.19	51.11	38.89
Single	40.65	44.74	47.45	41.58	45.83
Have Pension	25.23	24.44	24.91	21.69	20.83
Bank loan for housing	1.76	1.95	1.32	0.97	0.69
<b>B. Family Income (\$,2009 base year)</b>					
Non-housing Financial Wealth (mean)	1013	1777	1098	1020	1390
(median)	82	86	100	136	99
Transfers from Children (mean)	579	530	472	546	567
(median)	170	236	211	258	421
<b>C. Health Status (%)</b>					
Healthy	41.64	40.30	38.66	40.47	51.39
Disabled	21.51	21.39	22.91	19.75	24.31
Chronic Diseases	64.99	62.82	62.98	62.43	73.61
Smoke	11.20	11.82	11.11	10.22	12.50
Drink	13.31	15.03	12.71	10.64	12.50
Exercise	51.24	48.94	48.45	50.14	49.31
<b>D. Family Closeness (%)</b>					
Contact with children	61.90	67.25	62.52	67.68	52.78
See children frequently	72.35	69.83	65.07	65.33	61.11
Children live nearby	66.99	66.85	62.93	65.33	66.67

Table 5: City Level Summary Statistics

Mean Value	Group 1			Group 2			Group 3			Group 4			Never-Treated
	Before	After	Diff	Before	After	Diff	Before	After	Diff	Before	After	Diff	
<b>A. Health Status</b>													
Healthy	.	0.215	.	0.23	0.22	-0.01	0.185	0.205	+0.02	0.20	0.18	-0.02	0.25
<b>B. Health Care Utilization</b>													
Number of Nights for Hospitalization	.	1.90	.	0.89	1.96	+1.07	1.13	1.91	+0.78	1.37	2.82	+1.45	0.895
Whether received inpatient last year	.	0.14	.	0.09	0.17	+0.08	0.11	0.19	+0.08	0.12	0.25	+0.13	0.11
Whether received outpatient last month	.	0.203	.	0.20	0.22	+0.02	0.21	0.19	-0.02	0.243	0.20	-0.043	0.19
<b>C. Medical Spending</b>													
Inpatient OOP	.	43.22	.	11.30	68.43	+57.13	26.75	49.35	+22.6	26.78	125.42	+98.64	64.88
Outpatient OOP	.	13.0	.	9.07	17.19	+8.12	7.66	15.11	+7.45	25.52	18.59	-6.93	8.07
Medicines OOP	.	12.46	.	6.67	13.36	+6.69	5.98	14.14	+8.16	6.51	21.86	+15.35	11.50
<b>D. Family Transfers</b>													
Amount of transfers from Children	.	102.04	.	28.83	121.32	+92.49	57.06	104.64	+47.58	99.16	79.88	-19.28	68.99

### 3.3 Variables

I have an unbalanced individual-year panel data with 19,836 observations from 2011 to 2017. There are 35 variables totally in the sample to measure the observation's demographic information, health insurance and health care utilization, medical spending and family wealth. Four important dummy variables, URRMI, URBMI, NRCMI, UEMI, independently indicate whether or not a person enroll in one of these health insurance plans. Table 6 shows the sample size by health insurance plans and years, and the data is from CHARLS data codebook 2011, 2013, 2015 and 2017.

Table 6: Sample Size by Health Insurance Plans and Years (2011-2017)

Insurance	2011	2013	2015	2017
UEMI	1,912	2,353	2,910	2,848
URBMI	793	1,005	1,261	839 ↓
NRCMI	12,902	13,538	14,781	12,751 ↓
URRMI	224	366	498	2,397 ↑

**Dependent Variables:** Of the dependent variables, one subset is about the health care utilization, and I focus primarily on the following: whether or not the respondent had outpatient or visit last month, whether or not the respondent had inpatient or hospital stays last year and the total number of hospital nights last episode. The other set is about medical spending, including total medical spending as well as out-of-pocket (OOP) for inpatient health care, outpatient health care, and medicines. I summed up individuals' expenditure on modern over-the-counter medicine, prescription medicine, traditional medicine, vitamins, and health care equipment to obtain the total medicines expenditures. I used 2009 as the base year to adjust the nominal price to the real price and exchanged the Chinese Yuan for the U.S. dollar.

**Independent Variables:** Rather than impose a functional form, I use dummy variables  $D_{it}$  to express the treatment:

$$D_{it} = \begin{cases} 1, & \text{if in year } t, \text{ the city that individual } i \text{ lives in, implements the reform} \\ 0, & \text{if in year } t, \text{ the city that individual } i \text{ lives in, does not implement the reform} \end{cases}$$

I construct it by taking follow steps:

1. Tracing the changes in the number of enrollees for URRMI from 2011 to 2017 in each city (total: 125), and creating a city-year panel data;

2. Creating a dummy variable  $I_{ct}$  based on the step 1, and assign the variable 1 if the city  $c$  has zero number of enrollees for URRMI in year  $t-1$ , and meanwhile has a positive number of enrollees in year  $t$ ; otherwise assigning 0. For example, table 4 shows how to create the variable  $I_{ct}$ .

Table 7: Sample Size of URRMI and Dummy Variable  $I_{ct}$  (Subset)

City	Year	URRMI	$I_{ct}$	City	Year	URRMI	$I_{ct}$
Chengde	2011	0	0	Chuxiong	2011	1	1
	2013	1	1		2013	1	1
	2015	1	1		2015	1	1
	2017	54	1		2017	43	1

3. Merging the above city-year panel data with the individual-year panel data by individual’s living city, province, year; and then  $I_{ct}$  becomes the treatment variable  $D_{it}$  once I finish merging two datasets <sup>7</sup>.  $D_{it}$  represents the interaction term in Difference-in-Difference model.

I also create an alternative continuous treatment variable on city level, which allows me to run continuous treatment DD.

I also include covariables that indicate each observation’s gender, annual family income<sup>8</sup>, whether or not being disabled, having a chronic disease, whether received transfers from children and how much it is, whether or not doing any exercise, whether or not drink, and whether or not smoking. I select annual family income, rather than individual income, because consumption and wealth are usually distributed within a family in China <sup>9</sup>.

## 4 Identification

In an ideal quasi-experiment, participants are randomly assigned to either the treatment group or the control group. Both groups are asked about their health care utilization (or self-paid medical spending) at the baseline level. In the second stage, participants

<sup>7</sup>I rename  $D_{it}$  variable as “treat” in regressions

<sup>8</sup>It summed up all family member’s wage and bonus income. All income sources are adjusted to U.S.dollar based on 2009 CPI.

<sup>9</sup>For instance, grandparent’s (1<sup>st</sup> generation) out-of-pocket medical spending are usually afforded by parents (2<sup>nd</sup> generation) or grandchildren (3<sup>rd</sup> generation) in a Chinese family.

in the treatment group are assigned an intervention: They are required to enroll in the new integrated health insurance plan—URRMI. After the intervention, we measure all participants' health care utilization (or medical spending) and compare it with the baseline level. Finally, the comparison results could suggest whether URRMI impacts people's health care utilization (or medical spending) and how considerable this influence is. However, integrated health insurance is different from an ideal experiment from several aspects in practice.

Firstly, since eligible residents for URRMI voluntarily participate in the new health insurance plan, estimations should provide intent-to-treat effects. However, the way that I define  $D_{it}$  adjust the intent-to-treat to the normal two-way fixed-effects because  $D_{it}$  potentially assumes that all eligible citizens in the city  $c$  are treated in year  $t$  if the city  $c$  has zero number of enrollees for URRMI in year  $t - 1$ , and meanwhile has a positive number of enrollees in year  $t$ .

Secondly, the treatment time varies by city. In my sample, there are 46 cities that implemented the reform in the year 2011, 36 cities implemented in 2013, 26 cities implemented the reform in 2015, 12 cities implemented in 2017, and the rest 5 cities had not reformed in the last wave.

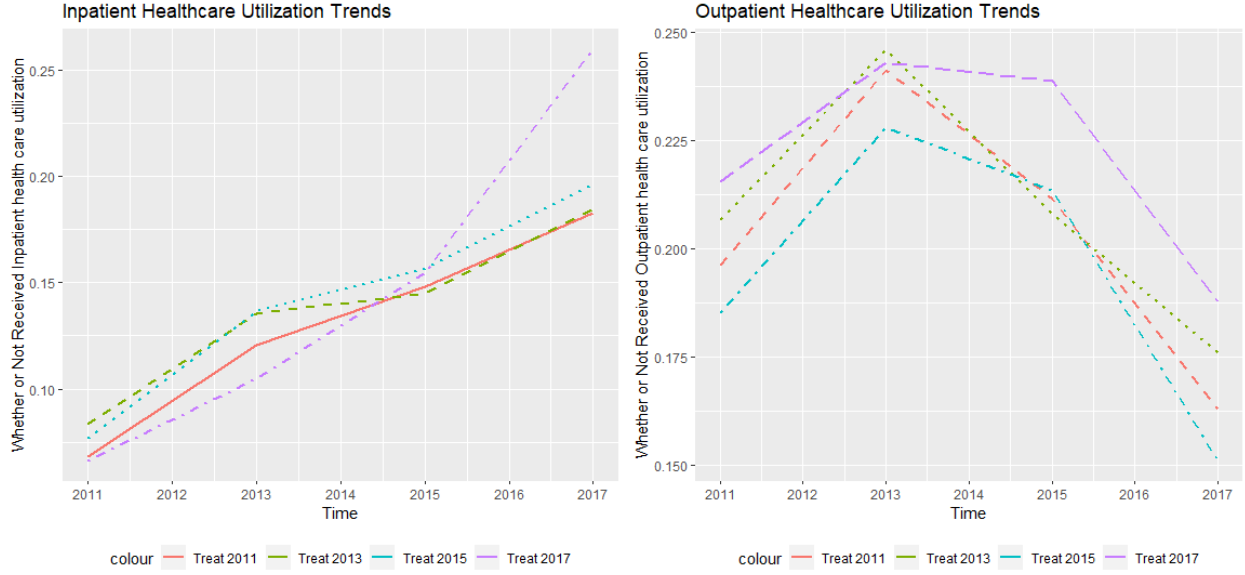
Thirdly, using sample data to infer the implementation year in each city potentially causes measurement error. For example, in table 7, there are two possible reasons to explain the zero number of enrollees for URRMI at Chengde city in 2011: Either Chengde City did not begin the reform in 2011, or Chengde City began the reform, but the enrollees are not included in our CHARLS sample. I ignore the latter case as running the regression so that it could cause bias.

## 4.1 Event Study

Figure 3 shows the inpatient and outpatient healthcare utilization changes over time by groups. The left panel of this figure shows the average probability of receiving inpatient healthcare utilization by different treatment groups. The graphs show that 2015 is a year threshold, and each treatment group almost all increased the chance of receiving inpatient healthcare after 2015. The right panel of this figure shows the average probability of receiving outpatient healthcare utilization by groups. In this case, 2013 seems to be an actual year threshold, and almost all groups decreased outpatient healthcare after 2013.



Figure 3: Inpatient Healthcare Utilization Trends



## 4.2 Two-Way Fixed-Effects

The paper tries to evaluate the integrated health insurance reform, so the first-order question is: What is the impact on the Chinese elder's out-of-pocket medical spending? As we discussed in the background, this reform aims to provide a more generous health insurance plan, so it is necessary to check whether the reform reduced individuals' OOP. The potential assumption is that individuals are sensitive to the price of medical care in China. Driven by this idea, I first study how the integrated health insurance reform affects the Chinese elder's OOP by estimating a two-way fixed-effect model. Next, we could study how the reform influences individuals' healthcare utilization.

$$Y_{it} = v_i + u_t + \delta \cdot D_{it} + \beta_X X_{it} + \epsilon_{it} \quad (1)$$

$Y_{it}$  measures out-of-pocket medical spending for inpatient health care and outpatient healthcare for individual  $i$  at year  $t$ ; and  $\delta$  measures the change in the out-of-pocket medical spending responding to the reform, holding other regressors constant.  $X_{it}$  includes control variables that are mentioned in section 3.3.  $D_{it}$  is the dummy variable that indicates whether the city that individual  $i$  lives in, implements the reform in year  $t$ .  $v_i$  is individual fixed effect, and  $u_t$  is the time fixed effect. However, there are many respondents reporting 0 medical spending, which caused left-skewness problem. To deal with the zero value problem in the medical spending, I used the two-part model-transformed OLS to solve it in Section 6, which is proposed by Buntin and Zaslavsky (2004) and Jones

et al. (2010).

Secondly, I employ the individual-year data to study the impact of integrated health insurance reform on the individual's inpatient and outpatient healthcare utilization by running the linear probability model with DiD regression, and the results are shown in section 5.

### 4.3 Probit Model

I estimate the probit model to study the impact of the integrated health insurance reform on individuals' healthcare utilization for inpatient and outpatient since the healthcare utilization is a dummy variable, either 1 or 0. The probit model is listed below. Firstly, the OLS regression function is:

$$Y_{it}^* = \delta \cdot D_{it} + \beta_X X_{it} + \epsilon_{it}$$

where  $\epsilon_{it} \sim N(0, 1)$ . Secondly, we could run ML to obtain the estimate  $\delta$ .

$$Pr(Y_{it} = 1|X) = \Phi(\delta \cdot D_{it} + \beta_X X_{it})$$

where  $Y_{it}$  measures inpatient health care and outpatient healthcare for individual  $i$  at year  $t$ ; and  $\delta$  measures the change in the probability of receiving inpatient health care and the probability of receiving outpatient health care, holding other regressors constant.

## 5 Results

### 5.1 Medical Spending

Table 8's columns 2 and 4 illustrate two-way fixed-effect estimation for Out-Of-Pocket medical expenditures for the inpatient and outpatient medical services. The reform caused inpatient out-of-pocket medical expenditure to decrease around 5 dollars and outpatient OOP to increase 4 dollars. Columns 1 and 3 show that the reform increases total medical spending by 4 dollars. However, all estimates are not statistically significant.

### 5.2 Healthcare Utilization

Table 9 reports the impacts of the reform on outpatient healthcare utilization under different control variables by estimating a probit model. Column 5 shows that the reform

Table 8: TWFE: The impact of the reform on medical spending

	<i>Dependent variable:</i>			
	inpatient_ms (1)	inpatient_oop (2)	outpatient_ms (3)	outpatient_oop (4)
Treat ( $D_{it}$ )	-11.739 (27.425)	-5.488 (14.521)	4.688 (9.178)	4.144 (5.548)
Control: Drink,Smoke,Exercise	✓	✓	✓	✓
Control: Disability, Chronic disease	✓	✓	✓	✓
Control: Family income, transfers	✓	✓	✓	✓
Observations	3,190	3,190	3,190	3,190
R <sup>2</sup>	0.009	0.006	0.007	0.007
Adjusted R <sup>2</sup>	-1.635	-1.643	-1.641	-1.641
F Statistic (df = 8; 1199)	1.405	0.944	1.069	1.045

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

could significantly increase the chance of receiving outpatient healthcare by 25.6% when we control the elder's demographic information and health status.

Table 9: Probit: Outpatient Healthcare Utilization

	<i>Dependent variable:</i>				
	outpatient				
	(1)	(2)	(3)	(4)	(5)
Treat ( $D_{it}$ )	-0.037 (0.032)	0.045 (0.037)	0.042 (0.053)	0.0001 (0.066)	0.256* (0.136)
Control: Demographic infor		✓	✓	✓	✓
Control: Self-reported Health			✓	✓	✓
Control: Family Income			✓	✓	✓
Control: Contact with Children				✓	✓
Control: Healthy behaviors					✓
Observations	10,332	6,068	3,245	2,055	464
Log Likelihood	-5,232.094	-3,183.323	-1,624.463	-1,051.184	-241.807
Akaike Inf. Crit.	10,468.190	6,376.646	3,260.925	2,118.368	505.614

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table 10 reports the impact of the reform on inpatient healthcare utilization. Column 1 shows that the reform leads to a significant increase in the chance of utilizing inpatient healthcare by 23% when there are no control variables. Column 5 shows that the reform significantly increases inpatient healthcare utilization by 37.4%. As the number of control variables increases, the treatment effect becomes more prominent.

The above results should be influenced by two factors: the reimbursement process in the public health insurance system and the cheap medical services for outpatient in

China. In China, the medical bills show the total medical expenditures. Even though a patient has enrolled in a health insurance plan, she must first pay the entire medical costs by herself. Then, she could take her medical bills and receipts to the local government to ask for the money return based on the coinsurance rate. In other words, to obtain health insurance coverage, a patient needs to go to the hospital first and then go to the local government. Since the amount of medical cost for outpatient healthcare is usually low (e.g., less than \$10 for a clinic visit), most patients do not want to waste time on traveling to the local government to get a small amount of reimbursement, even though they are facing a lower level of coinsurance rate after the reform.

Table 10: Probit: Inpatient Healthcare Utilization

	<i>Dependent variable:</i>				
	inpatient				
	(1)	(2)	(3)	(4)	(5)
Treat ( $D_{it}$ )	0.231*** (0.038)	0.160*** (0.045)	0.203*** (0.064)	0.248*** (0.080)	0.374** (0.177)
Control: Demographic infor		✓	✓	✓	✓
Control: Self-reported Health			✓	✓	✓
Control: Family Income			✓	✓	✓
Control: Contact with Children				✓	✓
Control: Healthy behaviors					✓
Observations	10,341	6,078	3,248	2,056	464
Log Likelihood	-4,081.186	-2,116.328	-1,124.781	-734.352	-144.326
Akaike Inf. Crit.	8,166.372	4,242.656	2,261.562	1,484.704	310.652

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

## 6 Robustness

### 6.1 DD with Continuous Treatments

Since the Two-way fixed effect with a dummy treatment variable shows that the reform has no significant impact on Chinese elders' out-of-pocket medical spending, I am considering whether running a TWFE with a continuous treatment variable makes any difference. The regression function is below.

$$Y_{it} = v_i + u_t + \delta \cdot D_{it}^c + \beta_X X_{it} + \epsilon_{it}$$

where  $Y_{it}$  could be out-of-pocket medical spending for inpatient health care and outpatient healthcare, inpatient healthcare utilization, or outpatient healthcare utilization for

individual  $i$  at year  $t$ ;  $D_{it}^c \in (0, 1)$  is a continuous treatment variable that measures the ratio between the number of treated individuals and the number of individuals in the city that  $i$  lives in in year  $t$ ; and  $\delta$  measures changes in the out-of-pocket medical spending responding to the reform, or changes in the healthcare utilization caused by the reform.

Table 20 reports that the reform with continuous treatment could statistically significant **reduce** individual's out-of-pocket medical spending for inpatient healthcare by \$5729. However, if we include any other control variables, the result is not significant anymore. Tables 12 and 13 reports the impact of continuous treatment on inpatient and outpatient healthcare utilization. Column 3 and 4 in table 11 shows that the continuous treatment could significantly reduce the probability that individuals receive outpatient healthcare by 2.25 ~ 2.56. Column 1 in table 12 shows that the reform also significantly reduces the chance of receiving inpatient healthcare by 0.06.

Table 11: TWFE: The Impact of Continuous Treatment on the Outpatient Healthcare Utilization

	<i>Dependent variable:</i>				
	outpatient				
	(1)	(2)	(3)	(4)	(5)
Continuous $D_{it}$	-0.020 (0.040)	-0.115 (0.092)	-2.246** (1.078)	-2.562** (1.133)	-0.000 (0.000)
Control: Demographic infor		✓	✓	✓	✓
Control: Family Transfers			✓	✓	✓
Control: Family Income				✓	✓
Control: Self-reported Health					✓
Observations	10,332	6,068	378	378	204
R <sup>2</sup>	0.00003	0.001	0.367	0.385	1.000
Adjusted R <sup>2</sup>	-0.335	-0.743	-6.694	-6.726	1.000
F Statistic	0.255 (df = 1; 7740)	1.016 (df = 4; 3477)	3.600** (df = 5; 31)	3.132** (df = 6; 30)	204.000*** (df = 7; 7)

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

## 6.2 DD with Multiple Time Periods

Given that the reform had different treatment timings, I use DD with multiple groups and periods to estimate Group-Time Average Treatment Effects (Callaway and Sant'Anna (2020)).

$$Y_{i,g,t} = \alpha + \beta G_g + \tau T_t + \gamma J_{g,t} + \eta X_{i,g,t} + \epsilon_{i,g,t} \quad (2)$$

Table 12: TWFE: The impact of Continuous Treatment on the Inpatient Healthcare Utilization

	<i>Dependent variable:</i>				
	inpatient				
	(1)	(2)	(3)	(4)	(5)
Continuous $D_{it}$	-0.060*	-0.046	0.162	0.079	-1.741
	(0.034)	(0.072)	(1.200)	(1.278)	(3.114)
Control: Demographic infor		✓	✓	✓	✓
Control: Family Transfers			✓	✓	✓
Control: Family Income				✓	✓
Control: Self-reported Health					✓
Observations	10,341	6,078	378	378	204
R <sup>2</sup>	0.0004	0.0004	0.191	0.192	0.608
Adjusted R <sup>2</sup>	-0.334	-0.742	-8.836	-9.148	-10.381
F Statistic	3.101*	0.378	1.466	1.192	1.548
	(df = 1; 7749)	(df = 4; 3487)	(df = 5; 31)	(df = 6; 30)	(df = 7; 7)

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

where  $Y_{i,g,t}$  could be healthcare utilization for individual  $i$  in group  $g$  in year  $t$ . In this case, I have four treatment groups, so  $g \in G_g = \{2013, 2015, 2017\}$ .  $J_{g,t}$  is equal to 1 if group  $g$  was treated at time  $t$ .  $X_{it}$  is a set of control variables. Since DD with multiple treatment timing requires the existence of pre-reform data, I exclude individuals who received treatment in 2011.

Table 13 reports the regression results, and there are no significant results found except Att(2013,2015) and Att(2017,2017). Figures 4 and 5 show the graphic results, and the red dots in the plots are pre-treatment pseudo-group-time average treatment effects and are most helpful in pre-testing the parallel trends assumption. The blue dots are post-treatment group-time average treatment effects and should be interpreted as the average effect of participating in the treatment for units in a particular group at a particular point in time. No obvious changes after the reform are found from the two figures.

### 6.3 Heterogeneous Effect

Table 14 reports the heterogeneous regression estimates, and we could find that the reform statistically significantly increased inpatient healthcare utilization for rural and non-working urban residents by 15.4% ~ 30.3%. Table 22 shows the heterogeneous effect on outpatient healthcare in the appendix, but no significant results are found.

Table 13: ATT(g,t) for Outpatient Healthcare Utilization

Group	Time	Outpatient		Inpatient	
		ATT(g,t)	Std Error	ATT(g,t)	Std Error
2013	2013	-0.1558	0.0781	0.0507	0.0455
2013	2015	-0.1667	0.0734	0.1156	0.0422*
2013	2017	-0.0584	0.0678	-0.1500	0.0811
2015	2013	-0.1521	0.0811	0.0604	0.0471
2015	2015	0.0130	0.0833	0.0757	0.0435
2015	2017	0.0875	0.0982	-0.1932	0.0794
2017	2013	-0.1667	0.0851	0.0387	0.0478
2017	2015	0.0222	0.0978	0.1053	0.0499
2017	2017	0.0889	0.0953	-0.2006	0.0788*

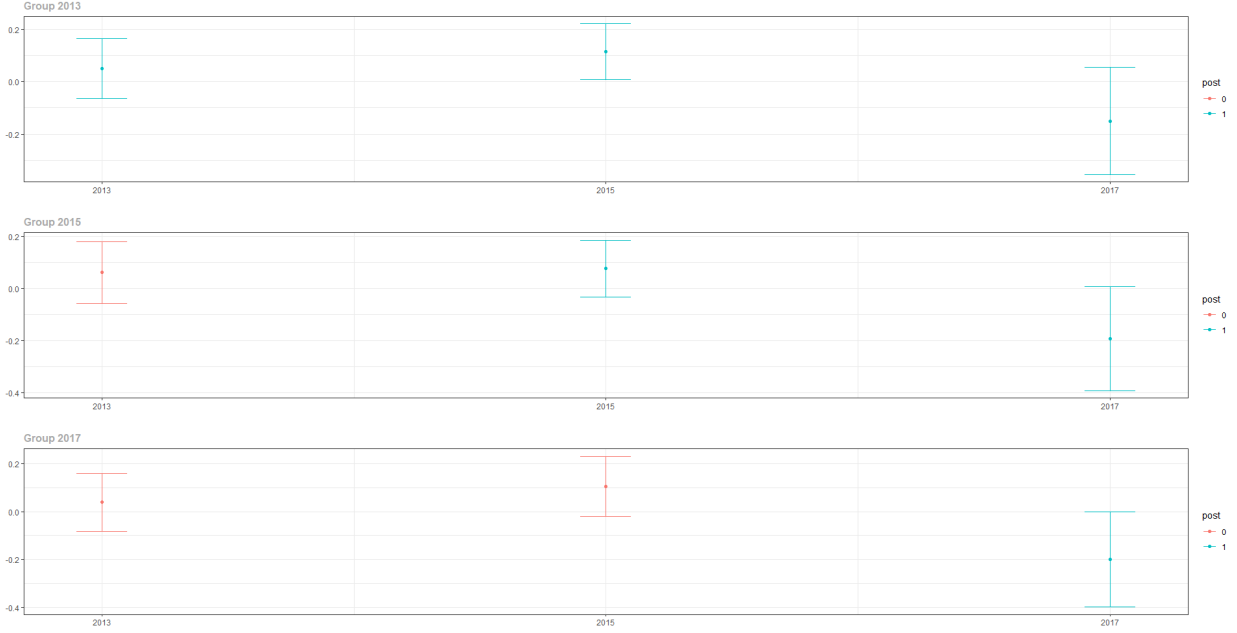
Table 14

	<i>Dependent variable:</i>					
	Inpatient					
	(1)	(2)	(3)	(4)	(5)	(6)
	Urban	Rural	Urban	Rural	Urban	Rural
$D_{it}$	0.154** (0.072)	0.260*** (0.045)	0.157* (0.088)	0.164*** (0.053)	0.119 (0.154)	0.303*** (0.095)
Demographic infor Health and Income			✓	✓	✓ ✓	✓ ✓
Observations	2,874	7,467	1,671	4,407	486	1,570
Log Likelihood	-1,087.782	-2,991.292	-560.533	-1,555.233	-183.833	-547.694
Akaike Inf. Crit.	2,179.565	5,986.583	1,131.066	3,120.466	383.666	1,111.389

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Figure 4: ATT(G,T) effect on Inpatient Healthcare Utilization



## 6.4 Left-Skewness

Figure 6 shows that the sample data of medical spending are left skewness, and I use the following methods to fix this problem.

I used two-part models to model cost data that include many zero values. The first part is the logit model, where

$$Prob(y_i > 0|x) = \Phi(x' \beta) = \frac{e^{x' \beta}}{1 + e^{x' \beta}}$$

where  $\Phi$  represents the logit distribution function that has heavier tails than the normal distribution. From the above equation, we could write down maximum likelihood's objective function:

$$L(\beta, \gamma) = \{1 - \Phi(x' \beta)\}^{i(i=0)} \times \{\Phi(x' \beta)g(x\gamma)\}^{i(y>0)}$$

where  $i$  denotes indicator function. Next, we take the log transformation on  $L$ , then we could obtain:

$$\log(L(\beta, \gamma)) = i(i = 0)\ln(1 - \Phi(x' \beta)) + i(y > 0)(\ln(\Phi(x' \beta)) + \ln(g(x\gamma)))$$

where  $g(x\gamma) = Prob(y|x, y > 0)$  After maximizing likelihood function, we could estimate



$\beta$  and  $\delta$ . The regression results are shown in table 25,26,27 and 28. However, there is no statistically significant results.

## 6.5 Zero Issue

I used log-transformation to deal with zero issues.

$$\log(1 + Y_{it}) = \beta \cdot D_{it} + v_i + u_t + \kappa_X X_{it} + \epsilon_{it}$$

$$\tilde{\beta} = 100 * [\exp(\hat{\beta}) - 1]$$

The log transformation equation is listed above. When dependent variables are transformed, predictions must be re-transformed back to the original scale to draw useful conclusions about the original variables. Table 23 shows the regression results for inpatient and outpatient total medical spending. The treat estimate for the inpatient medical spending is 0.045, and estimate for the outpatient medical spending is 0.004. Next, I used equation 1 to obtain an estimate with good interpretation, which gives me \$46 for inpatient, and \$0.4 for outpatient. It means that receiving treatment increase individuals in the treatment group total medical spending for the inpatient health care by \$46 than the individuals in control group, and similarly increase their total expenditure for outpatient health care by \$0.4.

Similarly, table 24 shows the regression results for out-of-pocket medical spending. The results implies that receiving treatment increase individuals in the treatment group self-paid medical spending for the inpatient health care by \$2.5 than the individuals in control group, and similarly increase their total expenditure for outpatient health care by \$2.7.

## 7 Conclusion

The integrated health insurance reform is a topic of increasing interest in China today, because the policymaker cares about whether this reform could indeed narrow the gap in health care utilization between rural residents and urban residents.

In this paper, I estimated the impact of this integration of health insurance plans on the Chinese elder's health care utilization and medical spending. To conclude, the reform significantly increased the elder's inpatient health care utilization by 16% ~ 37% but had no significant effect on the outpatient health care utilization. The results should be

influenced by the payment method in the public health insurance system and the cheap medical services for outpatient in China. In addition, I find no significant changes in out-of-pocket medical spending after the reform. Besides, no statistically significant results show the reform narrowed the rural-urban disparity in healthcare utilization.

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Zhu, K., Zhang, L., Yuan, S., Zhang, X., and Zhang, Z. (2017). Health financing and integration of urban and rural residents' basic medical insurance systems in china. *International journal for equity in health*, 16(1):1–8.

Figure 5: ATT(G,T) effect on Outpatient Healthcare Utilization

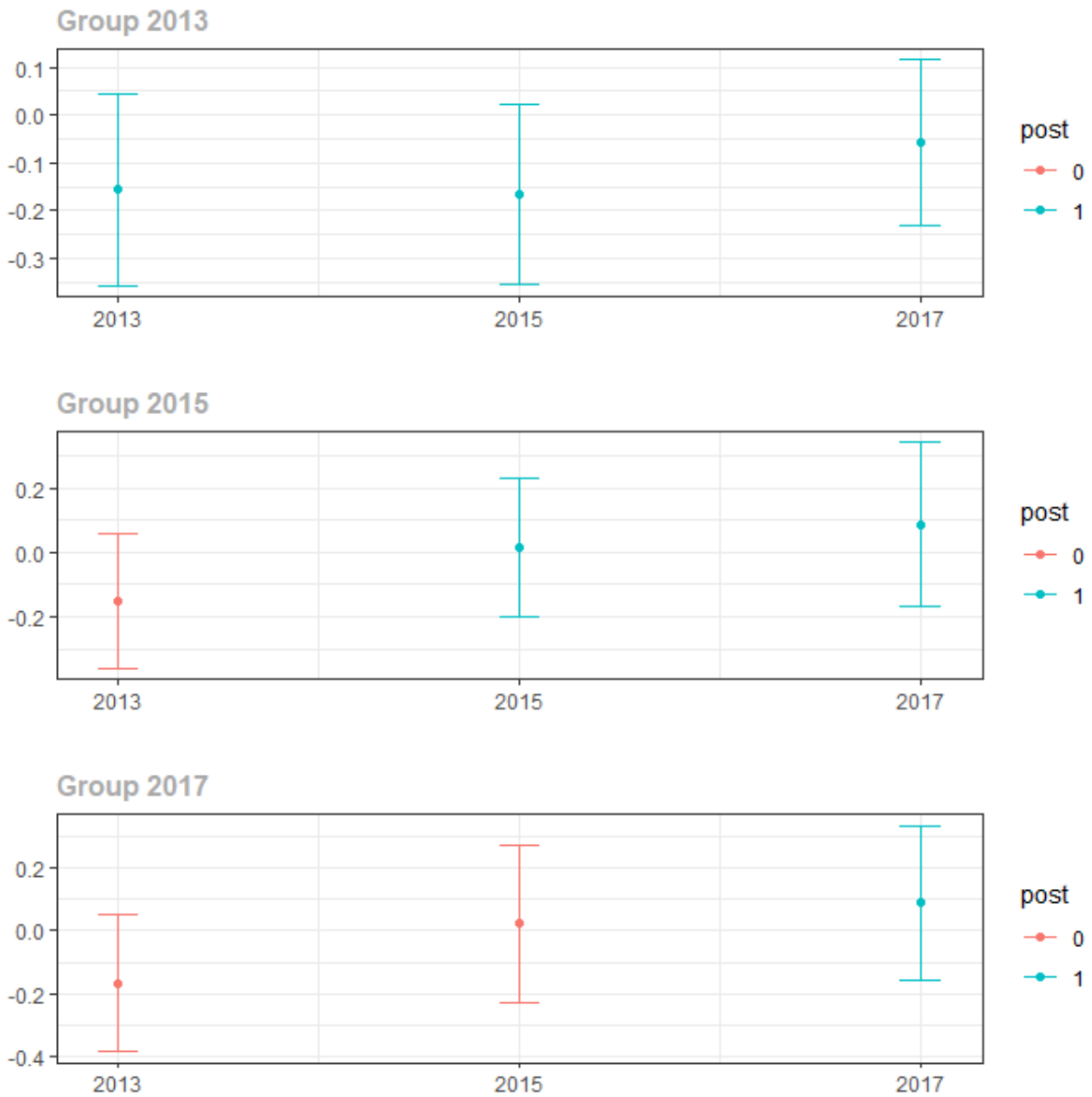


Figure 6: Density of Medical Spendings

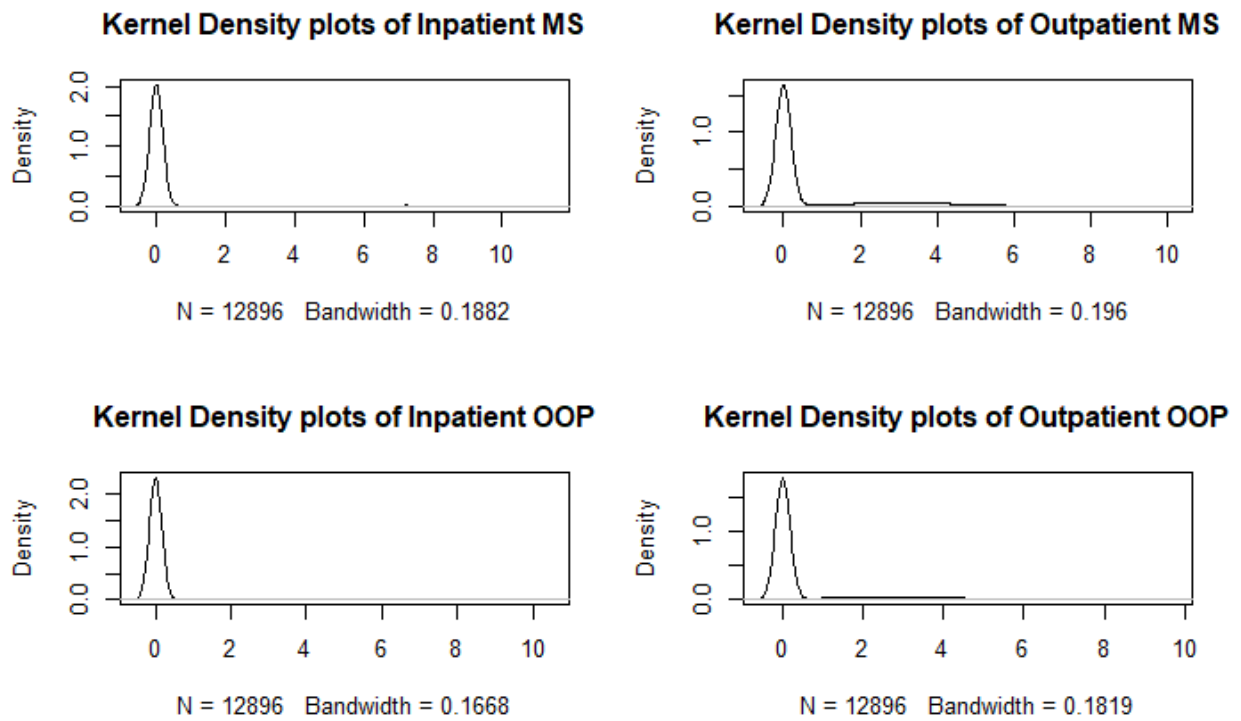


Table 15: Health Insurance Schemes in China: Jinan

Types	Before Integration		After Integration
	NRCMI	URBMI	URRMI
Start Year	2003	2007	2015
Enrollment Unit	Household	Household	Individual
Enrollment Type	Voluntary	Voluntary	Voluntary
Coverage Residents Live in	County/District (rural)	City (urban)	City, County and District (rural and urban)
Personal Paid Premiums (RMB/person)	630	Age ≤ 18 and College students: 80 Age ≥ 60 (or 55): 240 unemployed: 500	Two options: 300 or 100 300 or 100 300 or 100
Gov reimbursed premiums (RMB/person)	280	Age ≤ 18: 75 Age ≥ 60 (or 55): 385 unemployed: 125	
After Reform Premium Types		Type I: 300	Type II: 100
Gov reimbursed rate – Top Hospitals		40%	30%
Gov reimbursed rate – Middle Hospitals		65%	60%
Gov reimbursed rate – Low Hospitals		80 – 90%	80 – 90%

Table 16: Health Insurance Schemes in China: Liaocheng

Types	Before Integration		After Integration
	NRCMI	URBMI	URRMI
Start Year	2003	2007	2015
Enrollment Unit	Household	Household	Individual
Enrollment Type	Voluntary	Voluntary	Voluntary
Coverage Residents Live in	County/District (rural)	City (urban)	City, County and District (rural and urban)
Personal Paid Premiums (RMB/person)	630	Age $\leq$ 18: 80 Age $\geq$ 60 (or 55): 240 unemployed: 500	120 120 120
Gov reimbursed premiums (RMB/person)	280	Age $\leq$ 18: 75 Age $\geq$ 60 (or 55): 385 unemployed: 125	360 360 360
Gov reimbursed rate – Top Hospitals		53%	60%
Gov reimbursed rate – Middle Hospitals		53%	70%
Gov reimbursed rate – Low Hospitals		53%	80%



Table 17: Respondents Summary Statistics (2011-2017), %

Age	Total	Gender		Hukou		Living Area	
		Male	Female	Urban	Rural	Urban	Rural
≤ 50	25.77	23.42	27.91	23.79	26.56	27.35	24.18
51-55	15.49	16.00	15.02	14.06	16.07	15.11	15.87
56-60	19.00	19.32	18.69	18.68	19.12	18.65	19.34
61-65	13.88	14.78	13.07	14.13	13.78	13.19	14.58
66-70	9.62	10.20	9.08	9.82	9.53	9.02	10.21
71-75	7.17	7.84	6.56	9.51	6.23	7.64	6.70
76-80	4.67	4.73	4.61	5.32	4.40	4.60	4.73
≥ 80	4.41	3.71	5.05	4.69	4.30	4.44	4.38
Total	17,587	8,436	9,151	3,872	13,715	7,106	10,481

Table 18: Individual Level Summary Statistics

	Rural Switchers		Urban Switchers		Difference
	Mean	SD	Mean	SD	Mean
<b>A. Health Care Utilization</b>					
Number of Nights for Hospitalization	-0.24	0.21	0.64	0.66	0.87
Whether received inpatient last year	-0.02	0.01	-0.001	0.04	0.01
Whether received outpatient last month	-0.01	0.02	0.06	0.06	0.06
<b>B. Medical Spending (\$)</b>					
Inpatient MS	36.53	35.02	64.81	108.63	28
Outpatient MS	-1.71	4.21	21.68	13.43	28
Medicines MS	-1.16	1.12	0.9	3.57	2.0
Inpatient OOP	9.56	8.39	42.50	26.74	33
Outpatient OOP	-0.49	2.52	9.80	8.04	10
Medicines OOP	-1.65	1.07	0.77	3.41	2.42

Table 19

		<i>Dependent variable:</i>				
		Inpatient Nights				
		(1)	(2)	(3)	(4)	(5)
treat	-0.156 (4.039)	4.873 (5.002)	8.137 (6.554)	4.848 (10.827)	7.062 (11.569)	
age		-1.774 (1.215)	-2.080 (1.248)	-2.866 (2.437)	-2.689 (2.512)	
illiterate		3.367 (7.307)	4.476 (8.393)	-14.857 (17.486)	-12.257 (18.334)	
single		-7.882 (7.648)	-14.018* (7.569)	-63.077*** (15.118)	-62.178*** (15.559)	
healthy			0.713 (6.879)	7.260 (11.946)	6.478 (12.304)	
disability				-5.558 (15.894)	-2.320 (16.979)	
chronic disease				38.128 (21.232)	17.616 (37.210)	
Net Wealth					-0.001 (0.001)	
Observations	1,405	687	396	310	310	
R <sup>2</sup>	0.00000	0.047	0.270	0.677	0.691	
Adjusted R <sup>2</sup>	-2.304	-5.411	-8.299	-8.077	-8.544	
F Statistic	0.001 (df = 1; 425)	1.252 (df = 4; 102)	2.296* (df = 5; 31)	3.292** (df = 7; 11)	2.797* (df = 8; 10)	

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table 20

<i>Dependent variable:</i>					
Inpatient Times					
	(1)	(2)	(3)	(4)	(5)
treat	-0.166 (0.212)	0.021 (0.380)	-0.019 (0.643)	-0.249 (1.177)	0.054 (1.227)
age		0.002 (0.094)	0.137 (0.125)	-0.045 (0.284)	-0.021 (0.287)
illiterate		-0.628 (0.568)	-1.777** (0.843)	-0.710 (2.021)	-0.335 (2.071)
single		-0.205 (0.537)	-0.286 (0.760)	2.425 (1.773)	2.569 (1.789)
healthy			-0.148 (0.690)	1.235 (1.355)	1.146 (1.366)
disability				-0.277 (1.856)	0.216 (1.940)
chronic disease				-5.138* (2.473)	-8.334* (4.231)
Net Wealth					-0.0001 (0.0001)
Observations	1,434	709	402	316	316
R <sup>2</sup>	0.001	0.013	0.145	0.506	0.542
Adjusted R <sup>2</sup>	-2.260	-5.530	-9.718	-11.971	-12.111
F Statistic	0.612 (df = 1; 439)	0.358 (df = 4; 107)	1.083 (df = 5; 32)	1.755 (df = 7; 12)	1.628 (df = 8; 11)

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table 21: TWFE with Continuous Treatment, Inpatient OOP

<i>Dependent variable:</i>	
Inpatient OOP	
$D_{it}^c$	-5,728.384*** (1,569.271)
Observations	399
R <sup>2</sup>	0.146
Adjusted R <sup>2</sup>	-3.358
F Statistic	13.325*** (df = 1; 78)
<i>Note:</i>	*p<0.1; **p<0.05; ***p<0.01

Table 22

	<i>Dependent variable:</i>					
	Outpatient					
	(1)	(2)	(3)	(4)	(5)	(6)
	Urban	Rural	Urban	Rural	Urban	Rural
treat	-0.071 (0.061)	-0.025 (0.038)	0.050 (0.072)	0.044 (0.044)	0.060 (0.136)	-0.022 (0.076)
age			0.002 (0.004)	-0.001 (0.002)	-0.004 (0.008)	0.001 (0.004)
illiterate			0.065 (0.077)	0.047 (0.045)	-0.0002 (0.144)	-0.086 (0.075)
single			-0.027 (0.076)	0.094** (0.047)	0.142 (0.142)	0.091 (0.082)
healthy					-0.479*** (0.142)	-0.635*** (0.074)
NetWealth					-0.00000 (0.00001)	0.00000 (0.00000)
contact					4.077 (165.694)	0.209 (0.666)
Constant	-0.807*** (0.053)	-0.795*** (0.033)	-0.972*** (0.223)	-0.807*** (0.136)	-4.390 (165.695)	-0.634 (0.731)
Observations	2,873	7,459	1,668	4,400	485	1,570
Log Likelihood	-1,416.520	-3,814.245	-867.698	-2,314.613	-244.680	-804.788
Akaike Inf. Crit.	2,837.041	7,632.491	1,745.396	4,639.227	505.360	1,625.577

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table 23

	<i>Dependent variable:</i>	
	inpatient_ms.ln	outpatient_ms.ln
	(1)	(2)
treat	0.045 (0.075)	0.004 (0.093)
smoke	-0.662*** (0.144)	-0.124 (0.176)
drink	0.124 (0.084)	0.041 (0.103)
exercise	-0.085 (0.097)	-0.007 (0.119)
income	-0.00002 (0.00003)	-0.00003 (0.00004)
transfers	0.00000 (0.00002)	0.00000 (0.00003)
disability	0.511 (0.351)	0.966** (0.431)
chronic_disease	0.179 (0.306)	-0.084 (0.376)
Observations	5,076	5,076
R <sup>2</sup>	0.013	0.003
Adjusted R <sup>2</sup>	-1.514	-1.540
F Statistic (df = 8; 1992)	3.330***	0.786

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table 24

	<i>Dependent variable:</i>	
	inpatient_oop_ln	outpatient_oop_ln
	(1)	(2)
treat	0.025 (0.065)	0.027 (0.087)
smoke	-0.533*** (0.124)	-0.207 (0.165)
drink	0.113 (0.073)	0.037 (0.096)
exercise	-0.076 (0.084)	0.034 (0.111)
income	-0.00001 (0.00003)	-0.00002 (0.00004)
transfers	0.00000 (0.00002)	0.00000 (0.00002)
disability	0.482 (0.304)	0.950** (0.403)
chronic_disease	0.150 (0.265)	-0.082 (0.351)
Observations	5,076	5,076
R <sup>2</sup>	0.012	0.004
Adjusted R <sup>2</sup>	-1.517	-1.538
F Statistic (df = 8; 1992)	3.034***	0.954

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01



Table 25: Inpatient Medical Spending

	(1) nonzero	(2) inpatient_ms	(3) inpatient_ms	(4) inpatient_ms
<hr/>				
main				
age	0.0208 (2.09)	0.0271 (1.13)	0.0208 (2.09)	0.0208 (2.09)
treat=0	0 (.)	0 (.)	0 (.)	0 (.)
treat=1	-0.255 (-1.25)	-0.0867 (-0.23)	-0.255 (-1.25)	-0.255 (-1.25)
healthy=0	0 (.)	0 (.)	0 (.)	0 (.)
healthy=1	-1.422 (-3.60)	-1.918 (-4.06)	-1.422 (-3.60)	-1.422 (-3.60)
income	0.0000242 (0.29)	0.000403 (3.00)	0.0000242 (0.29)	0.0000242 (0.29)
Constant	-4.531 (-6.94)	2.391 (1.66)	-4.531 (-6.94)	-4.531 (-6.94)
<hr/>				
glm				
age			-0.0222 (-1.58)	-0.0222 (-1.58)
treat=0			0 (.)	0 (.)
treat=1			0.104 (0.41)	0.104 (0.41)
healthy=0			0 (.)	0 (.)
healthy=1			-0.184 (-0.36)	-0.184 (-0.36)
income			0.000316 (2.86)	0.000316 (2.86)
Constant			8.723 (9.59)	8.723 (9.59)
Observations	3855	3855	3855	3855

*t* statistics in parentheses

Table 26: Outpatient Medical Spending

	(1) nonzero	(2) outpatient_ms	(3) outpatient_ms	(4) outpatient_ms
<hr/>				
main				
age	0.00609 (1.45)	0.0129 (1.09)	0.00609 (1.45)	0.00609 (1.45)
treat=0	0 (.)	0 (.)	0 (.)	0 (.)
treat=1	0.0907 (1.05)	0.610 (2.60)	0.0907 (1.05)	0.0907 (1.05)
healthy=0	0 (.)	0 (.)	0 (.)	0 (.)
healthy=1	-0.901 (-7.51)	-1.408 (-5.29)	-0.901 (-7.51)	-0.901 (-7.51)
income	-0.0000134 (-0.42)	0.0000431 (0.57)	-0.0000134 (-0.42)	-0.0000134 (-0.42)
Constant	-1.684 (-6.23)	1.767 (2.31)	-1.684 (-6.23)	-1.684 (-6.23)
<hr/>				
glm				
age			0.00677 (0.55)	0.00677 (0.55)
treat=0			0 (.)	0 (.)
treat=1			0.477 (1.93)	0.477 (1.93)
healthy=0			0 (.)	0 (.)
healthy=1			-0.626 (-1.74)	-0.626 (-1.74)
income			0.0000850 (0.94)	0.0000850 (0.94)
Constant			3.711 (4.61)	3.711 (4.61)
Observations	3855	3855	3855	3855

*t* statistics in parentheses

Table 27: Inpatient Out-of-Pocket Medical Spending

	(1)	(2)	(3)	(4)
	nonzero	inpatient_oop	inpatient_oop	inpatient_oop
<hr/>				
main				
age	0.0230 (2.28)	0.0336 (1.43)	0.0230 (2.28)	0.0230 (2.28)
treat=0	0 (.)	0 (.)	0 (.)	0 (.)
treat=1	-0.206 (-0.99)	0.121 (0.32)	-0.206 (-0.99)	-0.206 (-0.99)
healthy=0	0 (.)	0 (.)	0 (.)	0 (.)
healthy=1	-1.382 (-3.49)	-2.119 (-4.28)	-1.382 (-3.49)	-1.382 (-3.49)
income	0.0000348 (0.43)	0.000418 (2.97)	0.0000348 (0.43)	0.0000348 (0.43)
Constant	-4.750 (-7.12)	1.075 (0.76)	-4.750 (-7.12)	-4.750 (-7.12)
<hr/>				
glm				
age			-0.0162 (-1.08)	-0.0162 (-1.08)
treat=0			0 (.)	0 (.)
treat=1			0.379 (1.39)	0.379 (1.39)
healthy=0			0 (.)	0 (.)
healthy=1			-0.248 (-0.43)	-0.248 (-0.43)
income			0.000251 (2.11)	0.000251 (2.11)
Constant			7.462 (7.73)	7.462 (7.73)
Observations	3855	3855	3855	3855

*t* statistics in parentheses

Table 28: Outpatient Out-of-Pocket Medical Spending

	(1)	(2)	(3)	(4)
	nonzero	outpatient_oop	outpatient_oop	outpatient_oop
<hr/>				
main				
age	0.00195 (0.46)	-0.0116 (-0.94)	0.00195 (0.46)	0.00195 (0.46)
treat=0	0 (.)	0 (.)	0 (.)	0 (.)
treat=1	0.0211 (0.24)	0.347 (1.45)	0.0211 (0.24)	0.0211 (0.24)
healthy=0	0 (.)	0 (.)	0 (.)	0 (.)
healthy=1	-0.922 (-7.48)	-1.085 (-4.11)	-0.922 (-7.48)	-0.922 (-7.48)
income	-0.0000404 (-1.18)	-0.0000225 (-0.29)	-0.0000404 (-1.18)	-0.0000404 (-1.18)
Constant	-1.426 (-5.19)	3.004 (3.76)	-1.426 (-5.19)	-1.426 (-5.19)
<hr/>				
glm				
age			-0.0179 (-1.49)	-0.0179 (-1.49)
treat=0			0 (.)	0 (.)
treat=1			0.225 (0.97)	0.225 (0.97)
healthy=0			0 (.)	0 (.)
healthy=1			-0.254 (-0.75)	-0.254 (-0.75)
income			0.0000457 (0.51)	0.0000457 (0.51)
Constant			4.973 (6.32)	4.973 (6.32)
Observations	3855	3855	3855	3855

*t* statistics in parentheses