Impact of China's Urban Resident Basic Medical Insurance on Health Care Utilization and Expenditure*

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Abstract

In 2007, China launched a subsidized voluntary public health insurance program, the Urban Resident Basic Medical Insurance, for urban residents without formal employment, including children, the elderly, and other unemployed urban residents. We estimate the impact of this program on health care utilization and expenditure using 2006 and 2009 waves of the China Health and Nutrition Survey. We find that this program has significantly increased the utilization of formal medical services. This result is robust to various specifications and multiple estimation strategies. However, there is no evidence that it has reduced out-of-pocket expenditure and some evidence suggesting that it has increased the total health care expenditure. We also find that this program has improved medical care utilization more for the elderly, for the low- and middle-income families, and for the residents in the relatively poor western region.

Keywords: Urban China, Health insurance, Health care utilization, Health expenditure

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1. Introduction

Since the Chinese economic reform in 1978, China has been experiencing conspicuous economic growth. However, the economic success of China does not necessary translate into social welfare gains for its citizens. For example, along with the economic growth, in rural areas we witnessed the dissolution of the Rural Medical Cooperative System, which was the cornerstone of the health care system in rural China. In urban areas, millions of workers lost their jobs as well as employment-related health insurance during the retrenchment of state-owned enterprises starting from the mid-1990s. To improve the poor state of health care in China, the Chinese government has been trying to build up a universal public health insurance system in its recent health care reform. This ambitious public insurance system consists of three key programs: the Urban Employee Basic Medical Insurance (UEBMI) for the urban employed, initiated in 1998; the New Cooperative Medical Scheme (NCMS) for rural residents, established in 2003; and the Urban Resident Basic Medical Insurance (URBMI), covering urban residents without formal employment.[1] The last of these, URBMI, is the focus of this paper.

After its pilot project in 2007, URBMI was rapidly expanded from 79 cities to 229 cities (about 50 percent of China's cities) in 2008, and to almost all cities by the end of 2009. This program covered 221 million persons in 2011 (NBS, 2012), amounting to around 16.5% of the Chinese population.

The main objective of this paper is to investigate the impact of URBMI on health care utilization and expenditure. Understanding the effects of URBMI, and comparing the effectiveness of the three major health care systems (UEBMI, NCMS, and URBMI), is an important endeavor. Each of these systems has its unique institutional setup, covers different populations, and has different levels of premium and reimbursement. The comparison exercise will provide insights into resource allocation,

[1] The enrollment rates are 80.7% for UEBMI, 90.0% for NCMS, and 63.8% for URBMI in 2008; these percentages increased to 92.4%, 96.6%, and 92.9% in 2010, respectively (Yip et al., 2012). In 2010, there were 237 million, 835 million and 195 million enrollees of UEBMI, NCMS and URBMI, respectively. Overall 1.27 billion out of a total of 1.34 billion persons were enrolled in these three public health insurance programs in 2010, see National Bureau of Statistics (NBS) (2011) and the National Development and Reform Commission (NDRC) (2011).

the effectiveness of different components of the health care policy, the role of subsidies, etc. Study of the effectiveness of each individual program is an important step toward this kind of comparisons.[2] Nonetheless, there is little empirical research on the effectiveness of URBMI, mainly because it started only 5 years ago, and the proper data is limited. The only available study which examines the impact of URBMI is Lin et al. (2009). Their study is based on cross-sectional data collected in December 2007, focusing on who are covered by URBMI, who gain from it in medical expenditure, and whether the enrollees are satisfied with it.

Internationally, different aspects of public health care systems are widely studied in the literature. For example, Currie and Gruber (1996a; 1996b; 1997; 2001) investigate the impact of the Medicaid expansion on health and health care in the United States, and find the expansion has improved the health of newborn children and has increased health care utilization by their mothers. Card et al. (2008) find that the rise of Medicare coverage has decreased health disparity and increased health care utilization by the elderly in the United States. Cheng (1997) and Chen et al. (2007) study the impact of the universal health care system in Taiwan, and find that it has significantly increased utilization of both inpatient and outpatient care services by Taiwanese elderly. However, most of these studies are of developed economies, with relatively high subsidy levels and generous policies. Literature on public health insurance in developing countries is relatively scarce. Given the different development stages, subsidy levels, and copayment policies, it would be insightful to compare findings from developing countries, like China, with findings from the developed countries.

Different from public health insurance systems in most developed economies, URBMI is a voluntary insurance program with heavy government subsidies. To estimate the impact of URBMI, we use panel data from the China Health and

[2] Several studies (Wagstaff et al., 2009; Lei and Lin, 2009; Yip and Hsiao, 2009; Sun et al., 2009) investigate the impact of NCMS on health care utilization and health care expenditure, and find that NCMS has had a positive impact on the health care utilization, but its impact on health care expenditure has been limited. Wang et al. (2006) focus on the question of adverse selection in NCMS, and finds evidence of adverse selection. Chen and Jin (2012) examine the linkage between NCMS and the health and education outcomes, and find that NCMS does not affect child mortality or maternal mortality, but improves child school enrollment.

Nutrition Survey (CHNS), which is a longitudinal survey project and has collected eight waves since 1989. The last two waves were collected in 2006 and 2009. This feature of the data and the timeline of the implementation of URBMI allow us to better control for unobservables and the selection-bias issue (e.g., Heckman, 1990), which is especially important in the context of enrolling in a voluntary health insurance plan.

Current treatment literature has moved away from homogeneous treatment effect and allows for heterogeneous treatment effects for different groups of individuals. If the treatment effect is heterogeneous, it is important to distinguish between different types of treatment effects, such as treatment effect on the treated, average treatment effect, marginal treatment effect, etc, as discussed in Heckman and Vytlacil (1999). In this paper, we are interested in the treatment effect on the treated, which is an important measure of the effectiveness of policy programs with voluntary participation, as is the case of URBMI. Lei and Lin (2009) and Wagstaff et al. (2009) also estimate treatment effect on the treated when they evaluate the impact of NCMS, the voluntary health insurance program in rural China.

Our main empirical strategy is the difference-in-differences (DID) approach at the individual level.[3] In order to assess the validity of that approach, we carry out two *placebo* tests, which provide strong supportive evidence for the validity of the assumptions in our DID models. Our results indicate that URBMI program has significantly increased the utilization of formal medical services; however, there is no evidence that it has reduced out-of-pocket expenditure. We also find that this program has improved medical care utilization more for the elderly, for low- and middle-income families, and for residents in the relatively poor western region. Our main results are robust to multiple estimation strategies, such as instrumental models, and to various specifications.

The remainder of the paper is organized as follows: In Section 2, we briefly introduce the current Chinese health insurance system, and pay special attention to the

[3] Lei and Lin (2009), Wagstaff et al. (2009), and Chen and Jin (2012) also rely on DID methods in their studies on the impact of NCMS.

institutional setup of URBMI. In Section 3, we describe the China Health and Nutrition Survey, define the main dependent variables and independent variables, and present descriptive statistics. In Section 4, we discuss our empirical strategies. Section 5 gives our main results for the whole sample as well as results for different age groups, income groups, genders, and regions. In that section, we also test the assumptions of the DID estimators and carry out a series of robustness checks. We conclude the paper with Section 6.

2. Urban Resident Basic Medical Insurance

Before 1998, there were two principal health insurance schemes for the urban population in China: Labor Insurance Scheme and Government Employee Insurance Scheme. Both schemes were employment-based and mostly were for employees in public sector, state-owned and collectively owned enterprises. The dependents of the urban workers, including their children, spouses, and parents, who had no employment-related health insurance, were eligible for partial coverage (Liu, 2002). Aiming to increase insurance coverage and to control health care costs, in 1998 the Chinese government launched a health insurance reform in urban China, and merged the dual system of labor insurance and government employee insurance into a new insurance scheme known as Urban Employee Basic Medical Insurance (UEBMI) (Xu et al., 2007), covering employees and retirees in both the public and private sectors.[4] One notable feature of the new scheme is that it does not cover the dependents any more. There were an estimated about 420 million urban residents who had been left uninsured because they had no formal employment (Yip and Hsiao, 2009).[5] To provide health protection for those urban residents not covered by the UEBMI, the Chinese government began to implement a large-scale health insurance program, URBMI in 2007.

[4] Since the reform, there has been a transition process from the old system to the new UEBMI. During our study period 2006–2009, the medical insurance scheme for the government employees still operated in parallel with the new UEBMI, but it had a shrinking coverage and was mainly for employees in government departments, state services, or institutions.

[5] The number of 420 million is over-estimated. As noted in footnote one that there were 195 million enrollees of URBMI, and there were only 70 million individuals not covered by any of UEBMI, NCMS and URBMI in 2010.

URBMI is a government-run voluntary insurance program operated at the city level. Following the broad guidelines issued by the central government, provincial and city governments have considerable discretion over the details. As a result, URBMI exhibits variations in design and implementation across cities. Basically, URBMI mainly covers urban residents without formal employment, including children, the elderly, and other unemployed urban residents (State Council, 2007). To address the problem of adverse selection associated with the voluntary nature of URBMI, some cities require participation in URBMI at the household level. But some cities still allow for enrollment at the individual level.

URBMI is financed by individual contributions and government subsidies shared between central and local governments. The individual contribution for URBMI differs across cities, but is lower than the UEBMI premium, and higher than the individual contribution for NCMS because of the greater expense of health services in urban areas (Lin et al., 2009). In 2008, the minimum government subsidy was 40 RMB per enrollee per year, including a 20 RMB subsidy from the central government for the enrollees in the poorer central and western provinces. For those with financial difficulties or a severe disability, there was an additional subsidy of no less than 10 RMB per child enrollee, and 60 RMB per adult enrollee, of which the central government provided 5 RMB per child enrollee and 30 RMB per adult enrollee in the poorer central and western provinces. The average premium of the pilot cities in 2007 was 236 RMB for adults and 97 RMB for children. On average, the subsidies from central and local governments accounted for about 36 percent of the financing cost for adults, and 56 percent for children (State Council Evaluation Group for the URBMI Pilot Program, 2008). The total amount of subsidies from all governmental sources has increased to 200 RMB per year in 2011 (NRDC, 2012).

Aiming at reducing poverty resulting from poor health or serious illness, URBMI is intended to mainly cover inpatient services and outpatient services for catastrophic illness, and typically does not cover general outpatient services, or covers them only for chronic or fatal diseases such as diabetes or heart disease in the more affluent provinces; but these principles are not always followed in practice. The benefit package exhibits considerable heterogeneity across cities. In most pilot cities, there are different reimbursement rules for inpatient services delivered at different levels of facilities, which are usually less generous for care delivered at higher-level facilities. The reimbursement cap for inpatient costs is about four times the average annual salary of local urban workers, and the average reimbursement level is around 45 percent (State Council Evaluation Group for the URBMI Pilot Program, 2008).[6]

3. Data and Variables

3.1 Data

We use data from the China Health and Nutrition Survey (CHNS), carried out by the Carolina Population Center at the University of North Carolina Chapel Hill and the National Institute of Nutrition and Food Safety in the Chinese Center for Disease Control and Prevention. The CHNS is an ongoing longitudinal project collecting rich information to study social and economic changes, especially in health and nutrition, and their effects on the economic, demographic, health, and nutritional status of both rural and urban Chinese population. The CHNS employs a multistage, random cluster sampling procedure to draw the sample from nine provinces in China, including coastal, middle, northeastern, and western provinces, which differ considerably in geography, economic development, public resources, and health indicators. These sampled provinces host approximately 45 percent of China's total population. In each sampled province, counties are initially stratified into low, middle, and high income groups, and then four counties are randomly selected, using a weighted sampling scheme. The provincial capital and a low-income city are selected when feasible. Villages and townships within the sampled counties, and urban and suburban neighborhoods within the sampled cities, are selected randomly.

The content of the survey is comprehensive, covering a wide range of individual, household, and community characteristics. The household/individual survey collects detailed data on medical care usage, health status, health insurance, health behaviors,

[6] For example, the reimbursement rates range from 40% to 90%, and the ceilings are from 25,000 RMB to 100,000 RMB, depending on the city, category of health care services, and service provider; see Lin et al. (2009).

economic status, and socio-demographic characteristics for the sampled households and household members. The community survey, which is answered by a community head or community health workers, provides unique information on public facilities, infrastructure, health care provision, and insurance coverage at the community level.

The CHNS survey has collected eight waves of data to date (1989, 1991, 1993, 1997, 2000, 2004, 2006, and 2009). For the purpose of this study, we mainly use the last two waves, and restrict the sample to residents with urban *Hukou* (urban resident registration) living in urban areas. We further restrict the main sample to the target population of URBMI, including children aged 0–18; current students aged over 18; the elderly (age 60 and over) who either are retired or have no job information and are not covered by the UEBMI or by government employee medical insurance; and adults who are unemployed or are temporary workers and not covered by the UEBMI or by government employee medical insurance. The final study sample consists of 3,003 observations, which is an unbalanced panel, including 1,576 in 2006, and 1,427 in 2009.[7] The main variables and summary statistics are in Table 1.

3.2 Dependent Variables and Key Independent Variables

The main dependent variables are health service utilization and health expenditure. Health service utilization is measured by a binary variable indicating utilization of any formal medical care (for all and for those who have been sick or injured) in the last four weeks, and a continuous variable of inpatient hospital days in the last four weeks.[8] There are two measures for health service expenditures: total health expense for the formal care in the last four weeks, including all expenses such as fees and expenditures for registration, medicines, treatment, hospital bed, etc.; and the out-of-pocket health expenses which are not reimbursed by health insurance.

The key independent variable is whether the respondent is enrolled in URBMI. From the CHNS data, no observations were in URBMI in 2006, and almost half of the

[7] We also exploit a non-target population and use the 2004 wave when we test the assumptions of our models and carry out a robustness check.

[8] It has to be noted that only 30 out of 3,003 respondents reported positive inpatient hospital days in the last four weeks. This limits our empirical strategies; it also helps to explain the insignificant effect of the URBMI enrollment on inpatient hospital days in most of our regressions.

observations were enrolled in URBMI in 2009; this allows us to utilize the DID approach. Therefore, we specify two main independent variables for our DID models: one indicating the time period after URBMI was implemented, defined as wave 2009; the other indicating the treated group, defined as those who were enrolled in URBMI in wave 2009. There are 690 respondents who participated in URBMI in wave 2009, and among them, 355 respondents were also surveyed in wave 2006, which form the sample of the treated group. The control group consists of those who were not enrolled in URBMI in 2009, including 737 respondents in wave 2009 and 1221 respondents in wave 2006.[9]

-----Table 1-------

As shown in Table 1, about 48 percent (690 enrollees vs.737 non-enrollees) of the study sample was enrolled in URBMI in 2009. There was no significant difference in health service utilization and expenditure between the treated and control groups in 2006, but the treated group was 6% more likely to utilize formal medical care than the control group in 2009.

Two cities and four counties were sampled from each province in the CHNS, and a total of 54 cities or counties (we refer both cities and counties as cities hereafter) from nine provinces each year in 2006 and 2009. We have exact location information for 48 of them.[10] Combining this location information with the lists of URBMI pilot cities authorized by China's Ministry of Labor and Social Security in 2007–2008, we are able to determine whether or not a sampled city in the CHNS implemented URBMI during 2007–2008. Among the 48 sample cities, 10 implemented URBMI in 2007 and 32 in 2008. They are referred to as URBMI cities in this paper. The remaining 6 cities implemented URBMI in 2009, and they are referred to as

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[9] We also conduct fixed effect estimation using balanced panel data 2006-2009, and the results (not reported here) are very similar to our main results.

[10] Although the CHNS does not release the exact location information for the sample areas, following the strategy in Chyi and Zhou (2010), we identify the sample cities and counties by comparing the reported total areas and populations of the counties or cities in the CHNS community survey data with the corresponding information from multiple yearbooks in China. There are six sample areas that cannot be identified, and are thus excluded from the analysis in Tables 5 to 6 when the indicator for city participation in URBMI is used in the regressions.

non-URBMI cities.[11]

Besides the DID approach, we also apply instrumental variable (IV) methods as a robustness check, and use URBMI cities as one of instruments for individual participation. The other two instrumental variables for individual take-up are two binary variables indicating whether the respondent's household members are covered by the UEBMI or by government employee medical insurance. We will discuss the rationale for choosing them as instrumental variables later.

3.3 Other Independent Variables

We also control for other covariates affecting health care utilization and expenditure in our study. Individual- and household-level variables include education level (illiterate, primary school, junior high school, senior high school, and college), total household income (inflated to Chinese RMB in 2009), and other demographic variables including age, gender, marital status, household size, and student status. Community-level variables include a binary variable indicating the presence of a health facility in the neighborhood; the average treatment fee for a common cold in the neighborhood (inflated to Chinese RMB in 2009), which proxies for the local price level of health care service; and the natural logarithm of the community urbanicity index developed by Jones-Smith and Popkin (2010), which reflects the development and urbanization level. Provincial dummies are controlled to capture unobserved regional differences.

4. Empirical Strategy: Difference-in-Differences Estimator

To estimate the impact of URBMI enrollment on health care utilization and expenditure, the main econometric approach we adopted here is to specify a reduced-form relationship and estimate a DID model with the treatment status defined at the individual level. The strategy is to track the outcomes of the enrollees (treatment group) before and after the introduction of URBMI, and then compare the

[11] All cities were required to implement URBMI by the end of 2009. In our sample, six sample cities (counties) initiated URBMI in 2009. Among them, four sample cities (counties) started URBMI in June or July, and two sample cities (counties) in December. The survey for CHNS 2009 was conducted from August to November. Due to the limited time lag, it is reasonable to treat these six cities (counties) as non-URBMI cities in our study.

changes in outcomes of the enrollees with the corresponding changes for individuals who never participated in URBMI (control group). The simple DID estimator may be expressed as

$$\Delta_{URBMI} = (\overline{Y}_{after}^{treated} - \overline{Y}_{before}^{treated}) - (\overline{Y}_{after}^{control} - \overline{Y}_{before}^{control}) \quad (1)$$

where Δ_{URBMI} indicates the effect of URBMI enrollment on the outcomes (i.e., health care utilization and expenditure). $\overline{Y}^{treatment}$ and $\overline{Y}^{control}$ represent, respectively, the sample averages of the outcome for the treated and control groups before and after the treatment, as denoted by the subscripts. One main advantage of the DID estimator in equation (1) is that it can control for unobservables which are time-invariant or which are time-variant but with common time trend between the treated and control groups.

To control for other observables that may affect the outcomes, we estimate the following regression model using the pooled sample from both 2006 and 2009:

$$Y_i = \beta_0 + \beta_1 After_i + \beta_2 Treat_i + \beta_3 After_i * Treat_i + \beta_4 x_i + \beta_5 \omega_j + \beta_6 \tau_k + \varepsilon_i \quad (2)$$

where *i* indexes individuals, *j* indexes communities, and *k* indexes provinces. Y_i is the outcome variable, i.e., health care utilization or expenditure, for observation *i*; $After_i$ is an binary indicator for observation *i* in wave 2009, the time period after the introduction of URBMI; $Treat_i$ is a binary variable for treatment status; x_i is a vector of observed individual or household characteristics; ω_j is a vector of community characteristics; τ_k is the provincial fixed effect; ε_i is a random error term. The coefficient β_1 of $After_i$ represents the common time-series change in the outcome for control and treated groups. The coefficient β_2 of $Treat_i$ measures the time-invariant difference between treated and control groups. The coefficient β_3 of the interaction of $After_i$ and $Treat_i$ is our primary interest. Under the assumptions of DID estimator discussed above, β_3 identifies the effect of URBMI on the enrollees, i.e., the treatment effect of URBMI on the treated. We will carry out tests for the underlined assumptions of the DID estimator later.

5. Empirical Results

5.1 Main Results

Table 2 presents the results for the impact of URBMI enrollment on health care utilization and expenditure using OLS (or logit when applicable) and DID estimators.[12] Marginal effects from the logit model are calculated and reported with standard errors in parenthesis. Panel 1 in Table 2 consistently shows that enrollment in URBMI has significantly increased the probability of individuals' utilization of formal medical services in the past four weeks by 4 or 5 percentage points. Among people who were sick or injured in the four weeks prior to the survey, we find a similar positive effect on formal health care utilization (panel 2), but less precisely estimated due to the small sample size.

Panel 3 indicates that there was no significant effect of URBMI enrollment on the number of inpatient days in the last four weeks. One of the main reasons for these insignificant findings is that the CHNS only asks information on inpatient service for the past four weeks, which results in very few inpatient incidences. There are only 30 people having positive inpatient days.

Panels 4 and 5 report results on health expenditures, and the dependent variables are natural logarithm of the expenses. In panel 4, we find no evidence that the URBMI take-up status has reduced out-of-pocket expenditure.[13] Results in panel 5 suggest that total health care expenditure was increased by about 15% due to URBMI enrollment, but these results are insignificant. The finding that URBMI has not reduced out-of-pocket spending is consistent with the existing literature on the impact of NCMS in rural China (e.g. Wagstaff et al., 2009; Lei and Lin, 2009; Yip and Hsiao, 2009). This result is partly due to the increase of formal health care utilization, and partly due to the fact that URBMI appears to make people more likely to use higher-level providers as we shown later.

-----Table 2-------

[12] We report only coefficients of primary interest here, for ease of exposition, except for the estimation for any formal care (see Table A1); but the full set of regression results is available from the authors upon request.

[13] We also consider the impact of URBMI on out-of-pocket expense for those who were sick or injured in the last four weeks, and for those users of formal medical care. The results (unreported here) are also insignificant.

5.2 Tests for DID Assumptions

To obtain a consistent estimate of the impact of URBMI from OLS, it is required that the enrollment be unrelated to unobserved individual characteristics that may directly affect health care utilization and expenditure. In other words, there should be no omitted variable bias or self-selection. In the health insurance literature, adverse selection is always a serious concern. The DID estimators relax this requirement to some degree. If the unobservables are time-invariant or time-variant but have common time trend in treated and control groups, DID still estimates the causal effect of URBMI for the enrollees consistently. However, from columns (3) and (4) of Table 1, we can see that the observable characteristics of the treated group differ significantly from those of the control group in both 2006 and 2009. The treated group had lower incomes and was less educated, older, and more likely to be married than the control group in 2006. Although we control for the observables, unobserved time-invariant individual heterogeneity, and unobservables with common time trends through DID methods, it may still raise concern that there is a possibility that our findings are driven by time-varying unobservable characteristics with different time trends. Therefore, we conduct two placebo tests to examine the validity of the DID assumptions.

-----Table 3-------

We first obtain the analogous estimates of the impacts of URBMI using the 2004 and 2006 data. This period was before the implementation of URBMI, which started in 2007. Specifically, exploiting the panel nature of the data, we define the treatment status (the URBMI take-up status) using 2009 wave data as before, and then apply the DID estimators to the 2004 and 2006 data to estimate the effect of the (nonexistent) URBMI on health care utilization and expenditure in 2006. As shown in Table 3, the results suggest that there were no significant differences between the treated and the control in health care utilization and expenditure from our DID estimation. This means that our main findings in Table 2 are most likely to capture the effect of URBMI, and are not driven by the different time trends of unobservables between treated and control groups; otherwise, we should also observe significant results based on 2004 and 2006 data if the time trend instead of URBMI is responsible for our findings in Table 2.

There could be another story of adverse selection: that people choose to participate in the program because they are expecting deterioration of their health in the foreseeable future, and this cannot be observed by the researchers. Under this scenario, the enrollees would utilize more health services than non-enrollees even if URBMI had no effect. If this is the case, then the results from our DID models could be biased. In order to address this possibility, we carry out another placebo test, which uses the utilization of preventive medical services as the dependent variables in our DID models. The rationale is that if the above story is true, then the enrollees should utilize more health services whether they are covered or not covered by URBMI. Preventive medical care is typically not covered by URBMI. There are two specific types of preventive care: general physical examinations, and other preventive care for specific conditions, such as blood tests, blood pressure screening, vision and hearing examinations, prenatal examination, and gynecological examination. Table 4 gives analogous estimates for uncovered preventative care, using 2006 and 2009 data. All results consistently show that the enrollees of URBMI did not differ significantly from the non-enrollees in the probability of using preventive care services.

-----Table 4-------

The above two placebo tests are obviously not proof of the exogeneity of URBMI enrollment, but they suggest that any potential bias in our main results stemming from adverse selection and non-constant unobserved heterogeneity must be small, which provides strong evidence to support the validity of our DID estimates.

5.3 Robustness Check

In this subsection, we carry out three robustness checks. We first experiment with alternative definitions of treatment groups and control groups. Secondly we apply a triple difference (difference-in-differences-in-differences, DDD) approach to estimate the impacts of URBMI. Lastly we apply an instrumental-variable approach to deal with potential endogenous bias.

DID Estimation Using Different Treatment/Control Groups

In addition to the main sample, using information on individual enrollment status and cities' exposure to URBMI, we define different treated and control groups to test the robustness of our main results. One treated group and three control groups are defined as follows. The treated group only includes the enrollees in the URBMI cities.[14] Control group I includes target residents living in the URBMI cities who chose not to enroll. Control group II includes those living in the non-URBMI cities. Since all sample cities (or counties) had implemented URBMI by the end of 2009, there may be some residents who joined URBMI in control group II.[15] Thus, we exclude those enrollees from control group II, and obtain control group III.

The arguments in favor of the comparison between the treated and control group I are that people living in the same cities are more likely to have common time-series changes in health care access, expense, etc., than people living in different cities; the city fixed effects are the same for both treated and control groups, and there is no selection bias at city level. But this comparison may suffer from selection bias at the individual level, i.e. people living in the URBMI cities may select themselves into the program in part on the basis of unobserved individual characteristics that change over time. Comparison between the treated and control group II/III can alleviate the selection bias problem at the individual level, but may be vulnerable to bias from unobserved time-variant city-level characteristics.

Column (1) of Table 5 is the main results from column (3) of Table 2. Columns (2) to (4) summarize the results from the DID estimations using these alternative treated and control groups. In panel 1, we consistently find a significant positive effect of URBMI enrollment status on the probability of using formal health service, but of somewhat larger magnitude than for the main results in column (1). In panel 2, columns (3) and (4) show that URBMI has a positive effect on utilization of formal health care when we restrict the sample to those who were sick or injured in the past

[14] For our main results in Section 5.1, we include all enrollees in the URBMI and non-URBMI cities in the treated group.

[15] In CHNS 2009, out of a total of 690 enrollees in the study sample, there are 42 respondents reporting URBMI enrollment in non-URBMI cities where URBMI was introduced in 2009.

four weeks. Moreover, in columns (3) and (4) of panels 4 and 5 in Table 5, we find that, compared to those living in non-URBMI cities, the enrollees in URBMI cities had significantly higher out-of-pocket and total health care expenditure.

-----Table 5-------

Triple Difference Estimation

However, as discussed earlier, results in columns (3) and (4) may be biased due to unobserved time-variant city characteristics. To control for the unobserved heterogeneity of the URBMI and non-URBMI cities, such as health policies that are associated with individual health care access and expense, we apply a triple difference (DDD) approach. The idea is that target population and non-target population in the same city share same city-level heterogeneity; this heterogeneity affects the health care utilization and expenditure in a similar way for the target population and for the non-target population.[16] The city level heterogeneity can be differenced out between these two populations, and hence DDD can control for bias from unobserved time-variant city characteristics. Specifically, we estimate the following DDD model using the sample of both target population and non-target population:

$$\begin{aligned} Y_{it} &= \beta_0 + \beta_1 After_t + \beta_2 Treat_{it} + \beta_3 TP_{it} \\ &+ \beta_4 After_t * Treat_{it} + \beta_5 After_t * TP_{it} + \beta_6 Treat_{it} * TP_{it} \\ &+ \beta_7 After_t * Treat_{it} * TP_{it} + \beta_8 x_{it} + \beta_9 \omega_{jt} + \beta_{10} \tau_k + \varepsilon_{it} \end{aligned} \quad (5)$$

where *TP* is a binary variable indicating the target population of URBMI. The non-target population includes those insured in the UEBMI in CHNS 2006–2009, who have ages in the range from 19 to 89. In order for the target sample to be comparable with the non-target sample, we exclude from the former all children under age 18 (268 observations). The coefficient β_7 measures the impact of the URBMI program.

The results from this DDD approach are in columns (6) and (7) of Table 5. Consistent with column (1), the results in column (6) and (7) show that the

[16] As shown in column (5) of Table 5, we also conduct DID estimations for non-target sample, with the treated group defined as those living in URBMI cities and the control group defined as those living in non-URBMI cities. We find no significant difference in health care utilization and expenditure between these two groups.

implementation of URBMI significantly increased access to formal health care, by 11 percent, for the enrolled target population. However, the previous significant results on out-of-pocket expenditure disappeared; the significant and positive results on total expenditure remain unchanged. In any case, the overall pattern of the results based on DDD models suggests that our main results are robust.

Instrumental Variables Estimation

For the last robustness check, we further deal with the potential endogeneity of URBMI enrollment by the IV method. Our instrumental variables include URBMI cities during 2007–2008, a dummy indicator for individuals with family members insured in UEBMI, and a dummy indicator for individuals with family members covered by government employee medical insurance.

Since only registered residents in the project cities are eligible for the program in most cases, individual take-up status is highly correlated with the introduction and the time of URBMI at the city level. In our sample, the enrollment rate was about 53% in URBMI cities and 25% in non-URBMI cities in 2009. Besides, the URBMI cities were mainly selected by the provincial governments, and the city governments were implementing URBMI following the policy guidelines issued by the central government. It is reasonable to assume that the selection of the URBMI city is exogenous to individuals.

Under the current health care system in China, most cities have individual medical savings accounts for UEBMI enrollees. These UEBMI enrollees may use their own account to buy drugs from pharmacies for their uninsured household members. Therefore, individuals with household members insured by UEBMI may feel less need to take up URBMI. Besides, those uninsured individuals cannot use this account for formal medical care, because it is not allowed by policy and can be easily found out by the health care provider. It may be plausible to assume that the insurance status of other family members has no direct effect on individual formal health care utilization after controlling for the individual's own insurance status and socioeconomic characteristics. Furthermore, we also experiment with an indicator of family members' insurance status in government employee medical insurance as the instrument, because it is another main public insurance scheme in urban China, although there are no individual accounts in this scheme.[17]

The first stage results, presented in Table A2, show that people living in cities exposed to URBMI during 2007–2008 were significantly more likely to enroll than those in cities exposed to URBMI in 2009. Individuals with family members insured in UEBMI were significantly less likely to take up URBMI; however, family members' insurance status in government employee medical insurance has no significant impact on the URMBI take-up, which is consistent with the fact that this insurance scheme does not have an individual account.

We experiment with different combinations of these three variables as our instruments. As reported in Table 6, the instruments pass the weak instrument tests, and first-stage F-statistics are greater than 15 with p-values of 0.00 in most specifications. The over-identification tests show that the exogeneity of the instruments cannot be rejected at any significance level for most specifications except Panel 4, which is on the out-of-pocket expenditure. This is reasonable since the family members with other public health insurance, especially with UEMBI, can cover some medical expenses for other family members as discussed earlier, i.e. the public health insurance enrollment status of one family member can affect the medical expenditure of others directly.

Consistent with the main results in Table 2, the IV estimates in panel 1 of Table 6 show a similar positive effect of the URBMI take-up on access to formal health care, but of somewhat larger magnitude (0.18–0.19) and less significance (10 percent level). In Panel 2, IV estimations using wave 2009 show that participation in URBMI has also significantly increased formal medical care use for those who have been sick or injured in the last four weeks (significant at the 5 percent level). Looking at panels 4 and 5, we find that joining URBMI resulted in increased total health expenditures but had no significant impact on out-of-pocket expense.

-----Table 6-------

[17] Refer to section 2 for more background about the current health insurance system in urban China.

Taken together, the results of the above three robustness checks suggest that URBMI did not reduce out-of-pocket health expenditures. This finding is consistent with the study by Wagstaff and Lindelow (2008) on earlier urban health insurance schemes in China. There are two possible reasons. One is that URBMI enrollment made people more likely to use formal medical care, as we find consistently. Another reason, supported by the supplemental results in Table A3, is that URBMI also increased the probability of people seeking care from higher-level providers. Health care from a higher-level provider is usually more expensive and is reimbursed less.

The potential endogeneity of our IVs as discussed in previous paragraph casts some doubt on our IV results in Panels 4 & 5, but overall, our main findings that URMBI has increased utilization of formal health care but has not reduced the out-of-pocket expenditures are consistent throughout different model specifications and samples.

5.4 Heterogeneous Effects

In Table 7, we present heterogeneous effects of URBMI for different subpopulations, using the DID methods. First, in columns (1)–(3) we examine if URBMI enrollment has differential effects for children (0–17 years old), the elderly (60 and above), and adults (18–59 years old). We find that the elderly enrollees are 19 percent more likely to use formal health care at a 1% significance level. Adult enrollees have significantly more inpatient hospital days (0.22 day) in the last four weeks than adult non-enrollees. There is no evidence that URBMI enrollment has improved health care utilization for children.

-----Table 7-------

In columns (4)–(6), we stratify the sample by household income level – below the 30th percentile, between the 30th and 70th percentiles, and above the 70th percentile of the income distribution – and obtain the DID estimates for each subsample. The results reveal that participating in URBMI has significantly improved the probability of formal health service utilization (by 10 percent) and inpatient hospital days (by 0.27 day) for low-income groups. Medium-income groups also benefit from participating in the program, and the program has significantly improved their access to formal health care. Their total medical expenditure has also increased significantly. However, the effects are insignificant for high-income families. These findings are different from those of Wang et al. (2005) on the NCMS, but are consistent with those of Currie and Gruber (1996b) on the United States.

In columns (7) and (8) of Table 7, we estimate the effect of URBMI separately for males and females. We find that there is a significant positive impact of URBMI on access to formal care for males, but no such significant effect for female participants. A possible explanation is that males may have higher price elasticity of demand for medical care than females (Manning and Phelps, 1979).

In the last three columns, we investigate the differential effects of URBMI by regions: eastern, central, and western. The results show that the URBMI participants in the relatively poor western region are significantly more likely to use formal care. For participants in eastern and central China, we find no such significant positive effects. These findings are consistent with Liu and Tsegai (2011) on NCMS.

In all regressions in Table 7, we find no evidence that URBMI enrollment has reduced out-of-pocket expenditure for any subgroup. In eastern regions, the out-of-pocket expenditures have been increased by 29 percent (though significant at the 10% level). Consistent with increased utilization of formal medical care, we also find that the program participation has increased the total health care expense for medium-income groups, and for residents in the western region.

6. Concluding Remarks

Our major results are that URBMI has significantly increased the utilization of formal medical services. However, we find no evidence that it has reduced out-of-pocket expenditure. These results are robust to various specifications and multiple estimation strategies. In particular, the assumptions for our DID model have passed two placebo tests.

The finding that URBMI has not reduced out-of-pocket spending is not surprising, and is consistent with the existing literature on the impact of the NCMS in rural China (Wagstaff et al., 2009; Lei and Lin, 2009; Yip and Hsiao, 2009; Sun et al., 2009; Sun et al., 2010; Shi et al., 2010). This result is partly due to the increase of formal health care utilization, and partly due to the fact that URBMI appears to make people more likely to use higher-level providers, which is consistent with previous literature (Wagstaff and Lindelow, 2008). However, since URBMI only started five years ago, it is still too early to tell its long-term effects, such as the aggregate effect examined in Finkelstein (2007), which is six times larger than the effect estimated from individual studies like ours.

We also investigate heterogeneous effects of the program for different age groups, income groups, genders, and regions. The program has improved medical care utilization more for the elderly, for low- and middle-income families, and for urban residents in the relatively poor western region. Our findings on low-income families are consistent with the results of Lin et al. (2009), who also find that poor participants are more likely to feel relief of a medical financial burden.

This finding of increasing utilization of formal medical care but no improvement of inpatient services should be interpreted with caution. There is an important data limitation in this study that the CHNS only collects inpatient services information for the past four weeks at the time of survey. Since inpatient service is a rare event, collecting information only in the past four weeks instead of a longer time (e.g., 12 months in most surveys) prevents us from accurately estimating the impact of URBMI on inpatient services. Our results do not mean that URBMI has no effect on inpatient service use. In fact, most of our estimates for inpatient care are positive, though they are not significant, due to the small sample size.

This study is subject to an additional data limitation that we only study a limited set of outcome variables, and cannot explore the impact of URBMI on the frequency of formal medical care use, as well as supply-side responses. We also do not examine URBMI on health outcomes. Research on those issues promises to be fruitful in the future.

References

Card, D., Dobkin, C., Maestas, N. (2008), "The impact of nearly universal insurance coverage on health care utilization: evidence from Medicare," *The American Economic Review* 98(5): 2242–2258.

Chen, Y., Jin, G. Z. (2012), "Does health insurance coverage lead to better health and educational outcomes? Evidence from rural China," *Journal of Health Economics* 31(1): 1–14.

Chen, L., Yip, W., Chang, M.C., Lin, H.S., Lee, S.D., Chiu, Y.L., Lin, Y.H. (2007), "The effects of Taiwan's National Health Insurance on access and health status of the elderly," *Health Economics* 16(3):223–242.

Cheng, S.H., Chiang, T.L. (1997), "The effect of universal health insurance on health care utilization in Taiwan. Results from a natural experiment," *JAMA* 278(2):89–93.

Currie, J., Gruber, J. (1996a), "Health insurance eligibility, utilization of medical care and child health," *Quarterly Journal of Economics* 111(2): 431–466.

Currie, J., Gruber, J. (1996b), "Saving babies: the efficacy and cost of recent changes in the Medicaid eligibility of pregnant women," *Journal of Political Economy* 104(6): 1263–1296.

Currie, J., Gruber, J. (1997), "The technology of birth: health insurance, medical interventions and infant health," NBER Working Paper Series 5985.

Currie, J., Gruber, J. (2001), "Public health insurance and medical treatment: the equalizing impact of the Medicaid expansions," *Journal of Public Economics* 82(1): 63–89.

Chyi, H., Zhou, B. (2010), "The effect of tuition reforms on school enrollment in rural China," unpublished manuscript.

Heckman, J. J. (1990), "Varieties of selection bias," *American Economic Review* 80: 313–318.

Heckman, J. J., Vytlacil, E. (1999), "Local instrumental variables and latent variables models for identifying and bounding treatment effects," *Proceedings of the National Academy of Sciences of USA* 96: 4730-4734.

Finkelstein, A. (2007), “The aggregate effects of health insurance: evidence from the introduction of Medicare,” *Quarterly Journal of Economics* 1: 1–37

Jones-Smith, J. C., Popkin, B.M. (2010), “Understanding community context and adult health changes in China: development of an urbanicity scale,” *Social Science and Medicine* 71: 1436–1446.

Lei, X., Lin, W. (2009), “The New Cooperative Medical Scheme in rural China: does more coverage mean more service and better health?” *Health Economics*, 18: S25–S46.

Liu, Y. (2002), “Reforming China’s urban health insurance system,” *Health Policy* 60: 133–150.

Lin, W., Liu, G., Chen, G. (2009),“Urban Resident Basic Medical Insurance: a landmark reform toward universal coverage in China,” *Health Economics* 18 (S2): S83–S96.

Liu, D., Tsegai, D.(2011),“The New Cooperative Medical Scheme (NCMS) and its implications for access to health care and medical expenditure: evidence from rural China,” ZEF Discussion Papers on Development Policy, No.155.

Manning, W.G., Phelps, C.E. (1979), “The demand for dental care,” *The Bell Journal of Economics* 10(2): 503–525.

National Bureau of Statistics (2011), *Statistical Communiqué of the People's Republic of China on the 2010 National Economic and Social Development* (in Chinese).

National Bureau of Statistics (2012), *Statistical Communiqué of the People's Republic of China on the 2011 National Economic and Social Development* (in Chinese).

National Development and Reform Commission(2011), *Report on China's Economic, Social Development Plan to the Annual People’s Congress* (in Chinese).

National Development and Reform Commission (2012), *Report on China's Economic, Social Development Plan to the Annual People’s Congress* (in Chinese).

Shi, W., Chongsuvivatwong, V., Geater, A., Zhang, J., Zhang, H., Brombal, D. (2010), “The influence of the rural health security schemes on health utilization and household impoverishment in rural China: data from a household survey of western and central China,” *International Journal for Equity in Health* 9:7.

Sun, X., Jackson, S., Carmichael, G.A., Sleigh, A.C. (2009), "Catastrophic medical payment and financial protection in rural China: evidence from the New Cooperative Medical Scheme in Shandong province," *Health Economics* 18:103–119.

Sun, X., Sleigh, A.C., Carmichael, G.A., Jackson, S. (2010), "Health payment-induced poverty under China's New Cooperative Medical Scheme in rural Shandong," *Health Policy and Planning* 25(5): 419–426.

State Council (2007), *Instructions on Establishing the Urban Employee Essential Medical Scheme*, State Council Document No. 20 (in Chinese).

State Council Evaluation Group for the URBMI Pilot Program (2008), *Report on URBMI Pilot Programs* (in Chinese).

Xu, L., Wang, Y., Collins, C. D., Tang, S. (2007), "Urban health insurance reform and coverage in China using data from National Health Services Surveys in 1998 and 2003," *BMC Health Service Research* 7: 37.

Yip, W., Hsiao, W. (2009), "China's health care reform: A tentative assessment," *China Economic Review* 20: 613–619.

Yip, W., Hsiao, W., Chen, W., Hu, S., Ma, J., Maynard, A. (2012),"Early appraisal of China's huge and complex health-care reforms," *Lancet* 379: 833–842.

Wang, H., Yip, W.,Zhang, L., Wang, L.and Hsiao, W. (2005), "Community-based health insurance in poor rural China: the distribution of net benefits," *Health Policy Plan* 20: 366–374.

Wang, H., Zhang, L., Yip, W.and Hsiao, W. (2006), "Adverse selection in a voluntary Rural Mutual Health Carehealth insurance scheme in China," *Social Science & Medicine* 63: 1236–1245

Wagstaff, A., Lindelow, M. (2008), "Can insurance increase financial risk? The curious case of health insurance in China," *Journal of Health Economics* 27: 990–1005.

Wagstaff, A., Lindelow, M., Gao, J., Xu, L., Qian, J. (2009), "Extending health insurance to the rural population: An impact evaluation of China's new cooperative medical scheme," *Journal of Health Economics* 28: 1–19.

Table 1. Summary Statistics

	Full Sample		Wave 2006			Wave 2009		
			Treated	Control		Treated	Control	
Sample Size	3003		355	1221		690	737	
	Mean	S.D.	Mean	Mean		Mean	Mean	
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variables (in the last four weeks)								
Any formal medical care	0.13	0.34	0.15	0.13		0.16	0.10	***
Any formal medical care for the sick[a]	0.58	0.49	0.63	0.58		0.58	0.55	
Inpatient hospital days	0.10	1.25	0.05	0.07		0.19	0.08	
Total health expense	155.01	2621.23	49.67	148.85		152.62	218.19	
Out-of-pocket health expense	57.50	975.61	26.79	38.35		45.18	115.54	
Preventive care use	0.04	0.19	0.03	0.04		0.05	0.04	
General physical examination	0.02	0.15	0.01	0.02		0.02	0.02	
Other preventive care use	0.01	0.12	0.01	0.01		0.02	0.01	
Explanatory Variables								
Individual characteristics								
Enrolled in URBMI	0.23	0.42						
Education: primary school	0.16	0.37	0.19	0.14	*	0.19	0.15	***
Education: junior high school	0.30	0.46	0.26	0.30	*	0.32	0.30	***
Education: senior high school	0.21	0.41	0.18	0.24	***	0.21	0.19	***
Education: college	0.03	0.18	0.01	0.04	***	0.03	0.04	
Total household income (k)	36.96	62.45	24.13	30.73	***	43.21	47.66	
Age	41.86	23.54	45.37	40.27	***	47.32	37.68	***
Female	0.56	0.50	0.59	0.58		0.56	0.52	*
Married	0.56	0.50	0.63	0.54	**	0.64	0.49	***
Household size	3.51	1.47	3.63	3.46	*	3.46	3.61	
Student	0.20	0.40	0.16	0.23	***	0.16	0.22	
Community characteristics								
Any health facility	0.65	0.48	0.56	0.50	**	0.83	0.75	***
Treatment fee for a cold (k)	0.07	0.08	0.04	0.07	***	0.07	0.07	
Community urbanicity index	83.78	10.00	81.81	82.46	*	85.92	84.93	*
Instrumental Variables								
URBMI city	0.41	0.49	0.00	0.00		0.93	0.80	***
HH member has gov. insurance	0.11	0.31	0.09	0.11		0.10	0.11	
HH member has UEBMI	0.30	0.46	0.23	0.26	*	0.33	0.38	***

Notes:

a) The number of observations for this variable is 682 for the full sample.

b) Column (5) indicates if column (3) and column (4) are significantly different. Column (8) indicates if column (6) and column (7) are significantly different. * p<0.10, ** p<0.05, *** p<0.01.

c) The total household income and average treatment fee are inflated to the 2009 price level.

Table 2. Effect of URBMI Enrollment on Health Care Utilization and Expenditure

	OLS or Logit Wave 2009 *dy/dx*	OLS or Logit Waves 2006–2009 *dy/dx*	DID Waves 2006–2009 *dy/dx*
	(1)	(2)	(3)
1.Any formal health care in the last four weeks			
Effect of URBMI	**0.04****	**0.04****	**0.05****
	(0.02)	(0.02)	(0.03)
Observations	1402	2967	2967
2.Any formal health care for the sick in the last four weeks			
Effect of URBMI	0.07	0.06	0.08
	(0.07)	(0.06)	(0.09)
Observations	319	676	676
3. Inpatient days in the last four weeks			
Effect of URBMI	0.08	0.08	0.13
	(0.08)	(0.08)	(0.09)
Observations	1402	2967	2967
4.ln(*out-of-pocket* +1)			
Effect of URBMI	-0.03	-0.04	-0.05
	(0.07)	(0.07)	(0.10)
Observations	1402	2967	2967
5.ln(*total health expense* +1)			
Effect of URBMI	0.14	0.14	0.15
	(0.10)	(0.10)	(0.13)
Observations	1402	2967	2967

Notes:

a) Marginal effects are reported. Cluster-robust standard errors are reported in parenthesis; * p<0.10, ** p<0.05, *** p<0.01.

b) Logit model is used for binary dependent variables in panels 1 and 2.

c) Other control variables include individual characteristics such as education, household income, age, gender, marital status, household size, and student status; community characteristics such as the presence of any health facility, average cold treatment fee, and urbanicity index; wave dummies; and province dummies.

Table 3. Placebo Test I – Estimates Using 2004–2006 Data

	OLS or Logit Wave 2006 *dy/dx*	OLS or Logit Waves 2004–2006 *dy/dx*	DID Waves 2004–2006 *dy/dx*
	(1)	(2)	(3)
1.Any formal health carein the last four weeks			
Effect of URBMI	−0.01	-0.01	-0.00
	(0.02)	(0.02)	(0.02)
Observations	1565	3927	3726
2.Any formal health care for the sick in the last four weeks			
Effect of URBMI	-0.04	0.03	-0.12
	(0.07)	(0.06)	(0.09)
Observations	357	942	941
3. Inpatient days in the last four weeks			
Effect of URBMI	-0.06	-0.07	0.07
	(0.06)	(0.04)	(0.08)
Observations	1565	3729	3726
***4.*ln(*out-of-pocket* +1)**			
Effect of URBMI	-0.01	-0.05	-0.06
	(0.08)	(0.07)	(0.12)
Observations	1565	3729	3726
5.*ln*(total expense +1)			
Effect of URBMI	-0.02	-0.01	0.00
	(0.10)	(0.09)	(0.13)
Observations	1565	3729	3726

Notes:

a) Marginal effects are reported. Cluster-robust standard errors are reported in parenthesis; * p<0.10, ** p<0.05, *** p<0.01.

b) The treatment status and the URBMI enrollment status are defined based on CHNS 2006–2009.

d) Logit model is used for binary dependent variables in panels 1 and 2.

e) Other control variables include individual characteristics such as education, household income, age, gender, marital status, household size, and student status; community characteristics such as the presence of any health facility, average cold treatment fee, and urbanicity index; wave dummies; and province dummies.

Table 4. Placebo Test II – Estimates for Uncovered Preventive Care

	OLS or Logit Wave 2009 *dy/dx*	OLS or Logit Waves 2006–2009 *dy/dx*	DID Waves 2006–2009 *dy/dx*
	(1)	(2)	(3)
1. Preventive care use in the last four weeks			
Effect of URBMI	0.01	0.01	0.02
	(0.01)	(0.01)	(0.02)
Observations	1408	2972	2972
2. General physical examination in the last four weeks			
Effect of URBMI	−0.01	-0.01	0.00
	(0.01)	(0.01)	(0.01)
Observations	1171	2972	2972
3. Other preventive care use in the last four weeks			
Effect of URBMI	0.02	0.01	0.02
	(0.01)	(0.01)	(0.01)
Observations	1408	2972	2972

Notes:

a) Marginal effects are reported. Cluster-robust standard errors are reported in parenthesis; * p<0.10, ** p<0.05, *** p<0.01.

b) Logit model is used for binary dependent variables in each panel.

c) Other preventive health services include blood test, blood pressure screening, child health examination, gynecological examination, and others.

d) Other control variables include individual characteristics such as education, household income, age, gender, marital status, household size, and student status; community characteristics such as the presence of any health facility, average cold treatment fee, and urbanicity index; wave dummies; and province dummies.

Table 5. Robustness Check –Estimates Using Different Treatment/Control Groups

Waves 2006–2009	DID	DID	DID	DID	DID	Triple difference	Triple difference
Control	Unenrolled in URBMI &non-URBMI cities *N*=1929	Unenrolled in URBMI cities *N*=1,388	All in non-URBMI cities N=357	Unenrolled in non-URBMI cities N=287	Non-target sample in non-URBMI cities N=168	Column (3) + Column (5)	Column (4) + Column (5)
Treated	All enrollees N=1038	Enrollees in URBMI cities only N=849	Enrollees in URBMI cities N=849	Enrollees in URBMI cities N=849	Non-target sample in URBMI cities N=1780		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1.Any formal health care in the last four weeks							
Effect of URBMI	**0.05****	**0.06***	**0.13****	**0.11***	−0.03	**0.11***	**0.11***
	(0.03)	(0.03)	(0.06)	(0.06)	(0.08)	(0.07)	(0.07)
Observations	2967	2237	1206	1136	1948	2886	2823
2.Any formal health care for the sick in the last four weeks							
Effect of URBMI	0.08	0.06	**0.46*****	**0.35***	0.39	0.11	0.02
	(0.09)	(0.09)	(0.14)	(0.18)	(0.31)	(0.33)	(0.35)
Observations	676	513	274	255	493	734	717
3. Inpatient daysin the last four weeks							
Effect of URBMI	0.13	0.14	0.16	0.16	-0.06	0.41	0.43
	(0.11)	(0.11)	(0.10)	(0.10)	(0.23)	(0.27)	(0.27)
Observations	2967	2237	1206	1136	1947	2885	2822
***4.* ln(*out-of-pocket* +1)**							
Effect of URBMI	-0.05	0.06	**0.44*****	**0.36****	0.20	-0.04	-0.08
	(0.10)	(0.11)	(0.16)	(0.16)	(0.22)	(0.24)	(0.25)
Observations	2967	2237	1206	1136	1947	2885	2822
***5.*ln(*total expense* +1)**							
Effect of URBMI	0.15	0.21	**0.61*****	**0.50****	0.00	**0.64***	**0.63***
	(0.13)	(0.15)	(0.21)	(0.22)	(0.25)	(0.33)	(0.35)
Observations	2967	2237	1206	1136	1947	2885	2822

Notes:

a) Marginal effects are reported. Column (1) is the main results from Column (3) of Table 2.

b) Cluster-robust standard errors are reported in parenthesis; * p<0.10, ** p<0.05, *** p<0.01.

c) Logit model is used for binary dependent variables in panels 1 and 2.

d) Other control variables include individual characteristics such as education, household income, age, gender, marital status, household size, and student status; community characteristics such as the presence of any health facility, average cold treatment fee, and urbanicity index; wave dummies; and province dummies.

e) In column (5), we use those insured in the UEBMI in CHNS 2006–2009 as the non-target sample, who have ages from 19 to 89.

f) In column (6), to conduct triple difference, we exclude children under age 18 (268 observations) from the target sample in order to make itcomparable to the non-target sample as described in e).

Table 6. Robustness Check – Estimates from IV Methods

Instrumental Variables	Indicator of URBMI Cities	Indicator of URBMI cities: Indicatorfor whether household members have UEBMI.	Indicator of URBMI cities: Two indicatorsfor whether household members have gov. insurance or UEBMI.
	2SLS Wave 2009	2SLS Wave 2009	2SLS Wave 2009
	(1)	(2)	(3)
1.Any formal health care in the last four weeks			
Effect of URBMI	**0.19***	**0.18***	**0.18***
	(0.11)	(0.10)	(0.10)
Weak instrument test	*F*=40.57***	*F*=23.61***	*F*=15.84***
Over-identification test		*p*=0.83	*p*=0.89
Observations	1215	1215	1215
2.Any formal health care for the sick in the last four weeks			
Effect of URBMI	**1.07****	**0.82****	0.84**
	(0.53)	(0.36)	(0.38)
Weak instrument test	*F*=6.39**	*F*=5.39***	*F*=3.63**
Over-identification test		*p*=0.39	*p*=0.58
Observations	274	274	274
3. Inpatient days in the last four weeks			
Effect of URBMI	0.37	0.31	0.34
	(0.52)	(0.49)	(0.49)
Weak instrument test	*F*=40.57***	*F*=23.61***	*F*=15.84***
Over-identification test		*p*=0.76	*p*=0.74
Observations	1215	1215	1215
4. ln(*out-of-pocket* +1)			
Effect of URBMI	0.51	0.12	0.20
	(0.42)	(0.38)	(0.38)
Weak instrument test	*F*=40.57***	*F*=23.61***	*F*=15.84***
Over-identification test		*p*=0.01	*p*=0.002
Observations	1215	1215	1215
5. ln(*total health expense* +1)			
Effect of URBMI	**1.19***	**0.96***	**1.01***
	(0.61)	(0.55)	(0.55)
Weak instrument test	*F*=40.57***	*F*=23.61***	*F*=15.84***
Over-identification test		*p*=0.31	*p*=0.35
Observations	1215	1215	1215

Notes:

a) Standard errors are reported in parenthesis; * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

b) Other control variables include individual characteristics such as education, household income, age, gender, marital status, household size, and student status; community characteristics such as the presence of any health facility, average cold treatment fee, and urbanicity index; wave dummies; and province dummies.

Table 7. Effects of URBMI by Population Groups from DID Estimators

Sample	0–17	18–59	60 and above	Low HH income	Medium HH income	High HH income	Male	Female	Eastern China	Central China	Western China
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
1.Any formal health care											
Effect of URBMI	0.08	-0.00	**0.19*****	**0.10***	**0.08****	-0.05	**0.08***	0.04	0.08	0.04	**0.07***
	(0.07)	(0.03)	(0.07)	(0.05)	(0.04)	(0.05)	(0.04)	(0.04)	(0.06)	(0.04)	0.04
Observations	738	1481	748	1087	1101	779	1298	1669	841	1197	929
2.Any formal health care for the sick											
Effect of URBMI	0.27	-0.03	0.19	0.09	0.20	-0.20	0.17	0.05	-0.03	0.05	**0.29****
	(0.22)	(0.13)	(0.12)	(0.12)	(0.13)	(0.18)	(0.11)	(0.10)	(0.17)	(0.12)	(0.14)
Observations	101	260	307	320	218	138	259	417	180	296	200
3. Inpatient days											
Effect of URBMI	-0.01	**0.22****	0.05	**0.27***	0.16	-0.15	0.10	0.16	0.09	0.15	0.06
	(0.08)	(0.11)	(0.25)	(0.15)	(0.14)	(0.23)	(0.13)	(0.12)	(0.21)	(0.14)	(0.12)
Observations	738	1481	748	1087	1101	779	1298	1669	841	1197	929
4.ln(*out-of-pocket* +1)											
Effect of URBMI	0.19	-0.15	0.09	-0.14	0.15	-0.19	-0.07	-0.01	**0.29***	-0.17	-0.10
	(0.17)	(0.13)	(0.23)	(0.18)	(0.13)	(0.21)	(0.13)	(0.14)	(0.16)	(0.17)	(0.16)
Observations	738	1481	748	1087	1101	779	1298	1669	841	1197	929
5. ln(*total expense* +1)											
Effect of URBMI	0.32	-0.02	0.53	0.06	**0.43****	-0.12	0.19	0.13	0.19	-0.03	**0.42****
	(0.23)	(0.17)	(0.33)	(0.26)	(0.17)	(0.29)	(0.18)	(0.18)	(0.26)	(0.22)	(0.20)
Observations	738	1481	748	1087	1101	779	1298	1669	841	1197	929

Notes:

a) Marginal effects are reported. Cluster-robust standard errors are reported in parenthesis; * p<0.10, ** p<0.05, *** p<0.01.

b) Logit model is used for binary dependent variables in panels 1 and 2.

c) Other control variables include individual characteristics such as education, household income, age, gender, marital status, household size, and student status; community characteristics such as the presence of any health facility, average cold treatment fee, and urbanicity index; wave dummies; and province dummies.

Table A1. The Effect of URBMI on Any Formal Medical Care Use in Last 4 Weeks

	Wave 2009		Full Sample		DID	
	OLS	**Logit**	**OLS**	**Logit**	**OLS**	**Logit**
	(1)	(2)	(3)	(4)	(5)	(6)
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
Enrolled in URBMI	**0.04****	**0.40****	**0.04****	**0.40****		
	(0.02)	(0.18)	(0.02)	(0.17)		
		[0.04]**		**[0.04]****		
		(0.02)		**(0.02)**		
Treated×Wave 2009					**0.05***	**0.50****
					(0.03)	(0.25)
						[0.05]**
						(0.03)
Treated					-0.01	-0.10
					(0.02)	(0.18)
Wave 2009			-0.02	-0.21	-0.03*	-0.24
			(0.01)	(0.15)	(0.02)	(0.16)
Primary school	0.00	-0.01	-0.03	-0.16	-0.03	-0.16
	(0.03)	(0.24)	(0.02)	(0.16)	(0.02)	(0.16)
Junior high school	-0.01	-0.10	-0.06***	-0.50***	-0.06***	-0.51***
	(0.03)	(0.23)	(0.02)	(0.16)	(0.02)	(0.16)
Senior high school	-0.01	-0.07	-0.06***	-0.45**	-0.06***	-0.45**
	(0.03)	(0.29)	(0.02)	(0.19)	(0.02)	(0.19)
College	-0.03	-0.20	-0.07*	-0.45	-0.07**	-0.46
	(0.05)	(0.57)	(0.03)	(0.39)	(0.03)	(0.39)
Low household income	0.02	0.12	0.03**	0.30**	0.03**	0.30**
	(0.02)	(0.20)	(0.02)	(0.14)	(0.02)	(0.14)
High household income	-0.02	-0.24	0.00	-0.01	-0.00	-0.02
	(0.02)	(0.21)	(0.02)	(0.16)	(0.02)	(0.16)
Age 18–54	-0.09**	-0.93**	0.01	-0.12	0.01	-0.12
	(0.04)	(0.37)	(0.03)	(0.25)	(0.03)	(0.25)
Age 55 and above	0.02	0.04	0.12***	0.87***	0.12***	0.87***
	(0.04)	(0.34)	(0.03)	(0.23)	(0.03)	(0.23)
Female	-0.01	-0.07	0.01	0.05	0.01	0.05
	(0.02)	(0.17)	(0.01)	(0.12)	(0.01)	(0.12)
Married	-0.02	-0.16	-0.03*	-0.24*	-0.03*	-0.23
	(0.03)	(0.22)	(0.02)	(0.14)	(0.02)	(0.14)
Household size	-0.02**	-0.16**	0.00	0.01	0.00	0.01
	(0.01)	(0.06)	(0.01)	(0.04)	(0.01)	(0.04)
Student	-0.08**	-0.79**	-0.00	-0.04	-0.00	-0.04
	(0.03)	(0.31)	(0.02)	(0.22)	(0.02)	(0.22)
Any health facility	0.00	0.04	-0.02	-0.19	-0.02	-0.19
	(0.03)	(0.26)	(0.02)	(0.15)	(0.02)	(0.14)
Cold treatment fee	0.06	0.65	-0.01	-0.16	-0.01	-0.20
	(0.08)	(1.17)	(0.07)	(0.89)	(0.07)	(0.89)
ln(community	0.03	0.46	0.01	0.13	0.01	0.13
urbanicity)	(0.10)	(0.92)	(0.06)	(0.49)	(0.06)	(0.49)
Constant	0.08	-3.19**	0.07	-2.84***	0.07	-2.82***
	(0.12)	(1.29)	(0.08)	(0.72)	(0.08)	(0.72)
(Pseudo) R^2	0.06	0.08	0.07	0.08	0.07	0.08
Observations	1402	1402	2967	2967	2967	2967

Notes:

a) Marginal effects are reported in square brackets for key independent variables.

b) Cluster-robust standard errors are reported in parenthesis; * *p*<0.10, ** *p*<0.05, *** *p*<0.01.

c) Other covariates include indicators of provinces, which are not reported here.

Table A2. Logit Estimation for URBMI Enrollment Decision Using the CHNS 2009

	All Cities		Project Cities	
	(1)	(2)	(3)	(4)
URBMI city		0.33***		
		(0.04)		
Household member has gov.medical insurance		-0.03		-0.01
		(0.05)		(0.06)
Household member has UEBMI		-0.09**		-0.10***
		(0.03)		(0.04)
Primary school	0.06	0.07	0.06	0.06
	(0.05)	(0.05)	(0.05)	(0.05)
Junior high school	0.09**	0.09**	0.08*	0.08*
	(0.04)	(0.04)	(0.05)	(0.05)
Senior high school	0.06	0.05	0.01	0.02
	(0.05)	(0.05)	(0.05)	(0.06)
College	-0.04	-0.06	-0.10	-0.08
	(0.09)	(0.09)	(0.09)	(0.09)
Low household income	-0.05	-0.06	-0.07	-0.09**
	(0.04)	(0.04)	(0.04)	(0.04)
High household income	-0.04	-0.04	-0.05	-0.05
	(0.04)	(0.04)	(0.04)	(0.04)
Age 18–54	0.13*	0.13*	0.16**	0.15**
	(0.07)	(0.07)	(0.07)	(0.07)
Age 55 and above	0.27***	0.28***	0.29***	0.28***
	(0.06)	(0.06)	(0.06)	(0.07)
Female	0.01	0.02	0.01	0.02
	(0.03)	(0.03)	(0.03)	(0.03)
Married	0.09**	0.07*	0.07	0.07
	(0.04)	(0.04)	(0.05)	(0.05)
Household size	-0.02*	-0.01	-0.02	-0.02
	(0.01)	(0.01)	(0.01)	(0.01)
Student	0.09	0.09	0.10*	0.10*
	(0.06)	(0.06)	(0.06)	(0.06)
Any health facility	0.12***	0.09**	0.21***	0.19***
	(0.04)	(0.05)	(0.05)	(0.05)
Cold treatment fee	0.42**	0.37*	0.37*	0.45**
	(0.19)	(0.20)	(0.19)	(0.20)
ln(community urbanicity)	0.15	0.11	0.32*	0.39**
	(0.16)	(0.17)	(0.19)	(0.19)
Observations	1215	1215	1060	1060

Notes:

a) Marginal effects are reported.

b) Cluster-robust standard errors are reported in parenthesis; * *p*<0.10, ** *p*<0.05, *** *p*<0.01.

c) Other covariates include indicators of provinces and a constant, which are not reported here.

Table A3. Effect of URBMI Enrollment on Level of Provider

	Ordered Probit
Effect of URBMI	Wave 2009
Coefficient	**0.17***
	(0.10)
Marginal Effects	
No facility	−0.033*
	(0.018)
Village or town health center	0.009*
	(0.005)
County hospital	0.006*
	(0.003)
City hospital	0.017*
	（0.009）
Observations	1392

Notes:

a) Cluster-robust standard errors are reported in parenthesis; * p<0.10, ** p<0.05, *** p<0.01.

b) Other control variables include individual characteristics such as education, household income, age, gender, marital status, household size, and student status; community characteristics such as the presence of any health facility, average cold treatment fee, and urbanicity index; wave dummies; and province dummies.