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DO SOCIAL MEDICAL INSURANCE SCHEMES IMPROVE CHILDREN'S HEALTH IN CHINA?

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Do Social Medical Insurance Schemes Improve Children's Health in China?

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Abstract

This study investigates the causal impact of acquiring social medical Insurance on hospital utilisation and health status for children under 16 years old in China from 2010 to 2016. We consider the China Family Panel Studies (CFPS), a longitudinal database which allows us to control for the effect of unobserved individual heterogeneity by means of difference-in-difference regressions combined with matching regression techniques. Our findings suggest that participating in social medical insurance schemes significantly increases children's yearly hospital use, especially for children who come from rural China. Moreover, this increase is not significantly different for people who were not previously sick. It is also found that social medical insurance schemes have no effect or even a marginally negative effect on children's health status in some cases. We discuss some potential explanations for this result.

Keywords: China; Social Medical Insurance; Health Outcomes; Difference-in-difference; Propensity Score Matching.
Jel classification: I130: Health Insurance.

1. Introduction

Expanding social medical insurance schemes to uninsured children can be deemed as a very interesting policy strategy since its beneficial effects are expected to be more persistent in young compared to adult people. For example Moav (2005) proposes a theoretical model to explain the persistency of poverty as a result of lack of investment in children. The importance of Children as economic assets in developing economies has been also discussed to a large extend in other papers; see Galor (2005) and references therein. In spite of this concern, it is intriguing that the investigation of the causal impact of insurance policies on children health has received relatively little attention in the empirical research especially for developing countries.

Some most relevant studies about children health are focused on the US. They show that Medicaid expansion in children population made access to health care easier (Miller 2012), increased the probability of hospitalization (Currie & Gruber 1996; Dafny & Gruber 2000) and improved access to primary care (Miller 2012; Kaestner et al., 2001). As for health status, Medicaid expansion increased children's health status which was measured by mortality rate (Currie & Gruber 1996) and self-rated health (Miller 2012). According to these analyses, it is possible to conclude that Medicaid expansion has a positive effect on children's health outcomes.

However, studies are scarcer when the attention is turned to a developing country like China. Chen and Jin (2012) represent an important exception to this concern. They consider a large cross sectional database to estimate the impact of insurance for Chinese children in rural areas for the year 2006. Given the absence of longitudinal information, their empirical analysis is conducted by comparing the health status in counties where the policy was and was not applied to similar households with high and low probabilities of being insured. This methodology denoted as propensity score matching with difference-in-difference estimation (PSM with DID) is a highly insightful way to estimate the causal impact of insurance on children health status for cross sectional data. However, as the authors indicate, an important problem of this estimation is that the selection of similar individuals can only be based on observables while key non-observable variables could be very different by individuals in regions affected and not affected by the insurance policy. In this respect, a longitudinal database circumvents this problem as it allows for the identification of the same individual before and after the policy takes place.

Other relevant studies based on Chinese background have paid little attentions to the children population. Liu et al. (2002) found that there was a significant increase in outpatient visits by lower socioeconomic groups in response to the pilot experiment of the Urban Employees Basic Medical Insurance Scheme (UEBMI). Similarly, a study by Lei and Lin (2009) showed that enrolling in the New-Type Rural Cooperative Medical Scheme (NCMS) increased the probability of preventive care utilisation in rural China. More recently, Li and Zhang (2013) took a closer look at the impact of different kinds of insurance systems on the health outcomes of Chinese senior citizens in Zhejiang and Gansu provinces. They found that people with UEBMI and URBMI tended to use more medical services and people with NCMS did not increase utilisation of outpatient and inpatient services. However there is little reason to think that conclusions for adults can be extrapolated to children. Unlike adults, children usually do not take their own health decisions. Their demand for health attention could be also different as they are also more likely to be affected by common childhood illnesses and, in general, their health status depend at a large extend on their genetic features and direct care offered by their parents.

This paper seeks to fill this gap in the literature by examining the impacts of health insurance schemes on health care utilisation and health status among Chinese children who are under sixteen years old. To do so, we use a longitudinal database from the China Family Panel Studies (CFPS) conducted in 2010, 2012, 2014 and 2016 in order to estimate the causal impact of medical insurance on four health outcomes: hospital visit frequency in last one year, hospital visit frequency in last one month, sick frequency in last one month and current self-rated health status. There are at least four important features of our database to conduct this analysis. First, comparing to prior studies, our database has separate questionnaire for children under 16 years old which includes a rich individual-level information covering demographic and economic characteristics as well as education, social welfare and health outcomes. A second advantage is that dealing with a longitudinal database enables us to control for time-invariant individual characteristics as we can compare the same individual before and after the treatment policy was implemented. A third relevant aspect is that it covers twenty-five provinces which allows us to have a more comprehensive idea of the impact of the insurance schemes on health outcomes. Finally, a continually updated database permits us to look into the interaction between insurance schemes and health some years after the establishment of schemes. A follow-up study based on recent database can be relevant because more individuals are covered by the social medical insurance schemes currently and previous results cannot be generalised.

The econometric analysis is conducted under three different econometric methodologies, namely individual fixed effect (FE), difference-in-difference (DID), and propensity score matching with difference-in-difference (PSM with DID) estimations. To preview, it is found that social medical insurance schemes significantly increase hospital visit frequency in last year especially for children who come from rural area. However, we do not find evidence to support that participating in social medical insurance schemes improves children's health status.

This paper proceeds as follows. Next section describes the Chinese social medical insurance system. Section 3 presents our database and the variables considered in the paper. Section 4 discusses the econometric models considered in the paper. Main results are displayed and analysed in Section 5 and some concluding remarks follow in Section 6.

2. Background

The reform of China's social medical insurance schemes started at 1998 in order to deal with the influence of economic reforms which took place in 1980s. In urban China, before the reform of urban social medical insurance, children were covered by social medical insurance packages offered by their parents' employers. Government officials and workers of the state-owned enterprises were eligible for the Government Insurance Program (GIP) and the Labour Insurance Program (LIP), respectively. Their health insurances were paid by employers and medical expenses were reimbursed from the employers' pre-tax income (Gordon G et al., 1999). In addition to this, half of their children's medical expenses were also reimbursed by the employers (W. Chen et al., 2009). However, only 51% of urban population were beneficiaries of the insurance schemes of which 7% and 43% were covered by the GIP and the LIP, respectively by the end of the 1990s (Gordon G et al., 1999). A large number of children whose parents were not covered by the two types of insurance programs had to pay out of pocket for their health care. Regarding rural China, farmers could join the Cooperative Medical Insurance Scheme (CMS) with money from the local collective welfare fund and individual monthly premium payments before the insurance reform (Hsiao, 1984). The insurance scheme varied widely among different places, and most of the time, children were excluded from it.

In spite of this, the three insurance schemes mentioned above played an important role in improving children's health status and relieve household financial burden. However, health care cost increased sharply, barefoot doctors were exodus from rural medical service system and urban enterprises were also challenged by poor financial performance due to the economic reforms (Gordon G et al. 1999; Hsiao 1984). Farmers in rural China found more and more difficult to afford medical expenses for themselves and their children's (Feng et al., 1995). Employers in urban China were no longer able to cover half-medical expenses for their employee's children. Even the coverage of employees could not be guaranteed (Y. Liu, 2002). Therefore, a new insurance scheme, called the Urban Employees Basic Medical Insurance (UEBMI), was established in 1998 to cover medical costs for all the urban employees (State Council, 1998). However, children were excluded, which caused a sharp increase in the number of uninsured children.

The Chinese government started to notice the importance of children health care and two independent social medical insurance schemes, the New-Type Rural Cooperative Medical Scheme (NCMS) and the Urban Residents Basic Medical Insurance (URBMI), were established in rural China and urban China in 2003 and 2007, respectively. These schemes cover children and other uninsured individuals (State Council, 2003 & State Council, 2007). Before the establishment of these two insurance schemes, provinces might offer some insurance guidance for children. However, the organizers, coverages and insurance premiums varied dramatically (W. Chen et al., 2009), and no nationwide social insurance schemes were available at that time.

Currently, NCMS and URBMI are social medical insurance schemes obtainable to children and both of them are considered in our analysis. They have some features in common. Firstly, both of the two schemes are voluntary programs that are funded by enrolee's premiums and by subsidies from central and local governments. Secondly, they both require full household participation in principle, which means children are either included or excluded from the program depending on their parents' participation (Li & Zhang, 2013).[1] More specifically, the household insurance premium is family size multiple premium per capita. Thirdly, territory based insurance schemes require that only local residents are included. In addition to this, local designated hospitals usually offer relatively more convenient access to medical care and easier reimburse process comparing to local non-designated hospitals as well as hospitals in other areas.

Government contributions and individual premiums of both schemes are different depending on the region's economic status and each individual's economic situation. At the beginning of the establishment of the schemes, it was required by the central government

[1] Partial participation is also observed in reality due to household members migration or different registration types((Y. Chen & Jin, 2012).

that the total government subsidies for each NCMS enrolee and URBMI enrolee should not be less than 20 RMB and 40 RMB, respectively [2]. Then the subsidies from various levels of government have increased considerably to about 450 RMB in 2017, and the premiums paid by enrolees increased to about 180 RMB at the meanwhile (Yizhou, 2017; Zongli & Long, 2017). It should be noted that children can get extra government subsidy, which may cover full premium in two special cases. One is for children who are in Dibao Program which ensures minimum living standard for poor households; the other is for children with severe physical disability.

The reimbursement rates of both schemes vary according to the level of care. There are primary, secondary and tertiary care levels in the health care system and among them primary care levels offer the highest reimbursement rate, while tertiary care levels offer the lowest. Similar to the enrolee's premium and government subsidy, reimbursement rates are also dissimilar in different regions of China. The coverages of NCMS's related to inpatient and outpatient service medical costs are approximately 70% and 50%, respectively while the coverage of URBMI's related inpatient service medical costs is about 70% (The State Council Information Office of PRC, 2017). The URBMI also covers some outpatient chronic or fatal diseases (Li & Zhang, 2013).

There has been a big increment in the number of people who have taken medical insurance since the reform of social medical insurance system, which was started in 1998. Over 1.3 billion Chinese, which is 95% of the total population, have taken part in social medical insurance schemes (The State Council Information Office of PRC, 2017). Children account for 17% of the whole Chinese population and most of them also covered by the insurance schemes (The National Bureau of Statistics of PRC, 2016b).

Overall, the Chinese government has given high priority to children's health care in the last 20 years. Besides social medical insurance expansion in children population, China also established a childcare management system in 2001 in order to offer disease screening for new-born babies (State Council, 2001). The rates of child care management under 3 years old and 7 years old were 91.1% and 92.4%, respectively by 2016 (The National Bureau of Statistics of PRC, 2016c). In addition to this, the number of health care institutions per 1000 people has more than doubled since 1998. More specifically, there were 74 hospital beds per 1000 people in 2016 in contrast to 31 in 1998. Maternal and childcare service centres offer specific treatment for women and children. There were 3021 maternal and childcare service centres in 2016 and hospital beds increased from 0.6 per 1000 people in 1998 to 2 per 1000 people in 2016.

Given these backgrounds, we focus on NCMS and URBMI which are available for Chinese children. The following section provides detailed information of our database.

3. Data

This study uses data from the China Family Panel Studies (CFPS) conducted by Institute for Social Science Survey (ISSS) of Peking University. It officially launched its baseline survey in April 2010 and full-scale follow-up interviews took place every other year with the

[2] The exchange rate between the Chinese currency (RMB) and the US dollar at the study period was roughly 6.3 RMB for 1 dollar.

last one in 2016. It is representative of all family members of households in 25 provinces in Mainland China, which accounts for 94.5% of the total Chinese population.

The CFPS provides information at the individual, family and community level. Here we restrict our attention to individuals younger than sixteen years old. It is a longitudinal database as the same individual can be identified in different years, but some of them were dropped from the sample due to deaths, migration of members as well as move towards adult database when their ages were over 16. In addition to this, each year there were new individuals included in the sample for reasons such as marriage or divorce happened in the family. The CFPS sample is self-renewing based on the natural changes of the baseline Chinese families. Thus, it is in the ideal situation of no attrition over time. More detailed information about data collection on the CFPS database can be found in Xie & Hu (2014).

The four response variables taken into consideration are individual hospital visit frequency in last year, individual hospital visit frequency in last month, individual sick frequency in last month and self-rated health status. The yearly and monthly hospital visit frequency are measurements of health care utilisation, they include hospital visits due to illness, and exclude vaccination, routine physical examination, or other things alike. Monthly sick frequency and self-rated health status are measurements of health status. Self-rated health status seizes individual's own assessment of health. It takes values 1 to 5 which means individual's self-rated health status is excellent, very good, good, fair and unhealthy, respectively. We do not consider self-rated health status in 2010 because the meaning of their values was inconsistent with the other waves. As shown in Figure 1, the distributions of the four variables are clearly not normal as there is a large proportion of zeroes in yearly hospital visit frequency, monthly hospital visit frequency and monthly sick frequency which are 49.5%, 22.6% and 71.3%, respectively. Moreover, the mass of the distribution is concentrated in just a few numbers of discrete cases. As it will be discussed in Section 4, these two issues together suggest that a traditional linear OLS could not be the most suitable procedure for the analysis of these four variables.

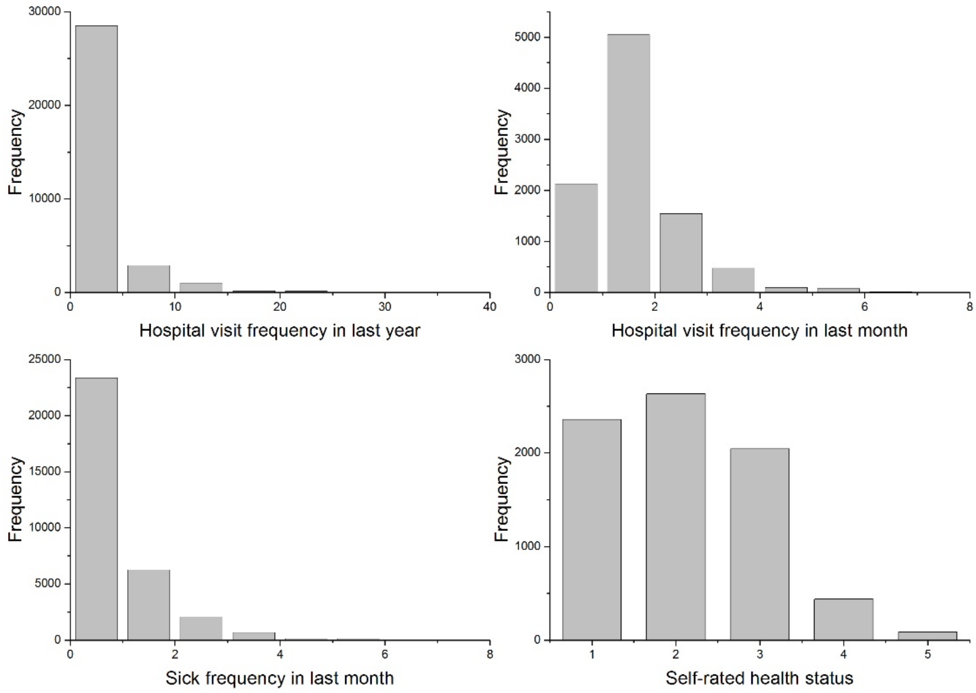

Figure 1 Distribution of response variables

Our treatment variable takes values 1 and 0 depending on whether or not the children have already participated in any of the two types of social medical insurance schemes: NCMS and URBMI. A figure of the dynamic evolution of the overall take-up rate is not shown for the sake of brevity. However, it can be mentioned that it shows a clear upward trend along time with the lowest take-up rate in 2012 (50.9%) and the highest in 2016 (85.3%) with an average value of 65.7%.

Control variables are split into two types: predisposing and enabling. Regarding the first group, some individuals are inclined to use medical care more than others do and this can be captured by the following individual characteristics: Age, Squared Age, Gender, Han (Ethnicity), Grade, Height and Weight. More specifically, the inclusion of Age can be justified because younger children may have a poor immune system which may result in more visits to the hospital. Moreover, parents may take different insurance purchase decisions along their children's age. Squared Age is used to model more accurately the effect of age because it could be non-linear. Regarding the inclusion of Gender, males are generally involved in more risky behaviour and females' mortality rate maybe high due to environmental disadvantages in remote areas (Waldron, 1983). Therefore, in principle, the influence of Gender on health is ambiguous. Regarding Ethnicity, although there are 56 ethnic groups in China, one of these groups, Han people, has the largest population. All the remaining groups are called minorities and they usually live in underdeveloped provinces with relatively primitive medical facilities which may lead to less health care utilisation and poor health status. According to this, we consider a simple binary ethnicity variable that takes value 1 for Han people and 0 otherwise. Grade is a categorical variable for children's education stage with values 1 to 5 which means nursery education, primary education, lower secondary education, upper secondary education and tertiary education, respectively. Students usually participate in some insurance schemes offered by school, having on average higher insurance coverage than children who have dropped out of schools. Weight and Height are traditionally important indicators for children's health.

Enabling variables are related to the availability of medical services. We include Income, Education Cost, Registration Type (Hukou) and Urban Area in this variable list. Income is measured by family's total income in last year. Parents have the financial ability to pay for their children's insurance premiums and health related services fee if they have high income. This means their children cannot only have more opportunities to get insurance products but also may have better health outcomes because of efficient health care treatments. Education Cost is measured by children's education cost per year. Typically, schools with high tuition fees sometimes offer special commercial insurances for their students. More importantly, Education cost also relates to family's income and they must be included together in the analysis. This variable could interact with treatment in two possible ways. First, a higher education cost may increase the financial burden of the families; therefore they may reduce their expenditure on insurance products. A second possibility is that a higher education cost indicates that children come from a higher social status and therefore they have the financial ability to get more insurance coverage. Registration Type (Hukou) is measured by child's current household registration type which includes agriculture registration and non-agriculture registration based on whether the household origin is rural or urban, respectively. This variable takes value 1 for agricultural registration and 0 for non-agricultural registration. Urban Area is defined by the children's current living area without considering their family origin. It equals to 1 when a child is in urban area currently and 0 otherwise. Hukou and Urban Area can identify the original area and migration of our sample. They are relevant as there are different social insurance schemes in the urban and rural China. In addition to this, many inhabitants who come from rural area originally and have agricultural registration come to the urban area seeking their fortune because of urbanization. Their children who attend school in urban area usually have no limitation of registration type when participating in social medical insurance schemes.

The common issue of microdata is the existence of missing values in different observations for different regressors. It imposes a serious limitation in the degrees of freedom of the regression. Due to this problem, we apply the EM algorithm to tackle data irregularities (Graham, 2009). It includes two steps: the expectation step and the maximisation step. In the expectation step, every variable with missing values is regressed on all other variables restricted to individuals with the observed variable. Year dummies and province dummies are also included in the imputation model for more precise imputation. And the missing values are substituted with the estimations from the regression model. This regression model varies with the type of variables with missing data. For continuous variables such as Income, Age, Squared Age, Weight, Height and Education Cost, we use linear regression models to impute the missingness. For binary variables like Urban Area, Hukou and Han logit models are applied. Finally, for Grade that is a categorical variable an ordered logistic model is applied. We follow Von Hippel (2007) for excluding response variables from the imputation models because artificial correlation between the control variables and response variables can contaminate our results. In the maximisation step, the missing values are substituted again by repeating the regression. This process is repeated iteratively for every variable until the likelihood ratio reaching convergence.

Table 1 shows the main statistics of the variables by insurance before and after the EM imputation procedure has been applied. The 'Uninsured', 'Insured' and 'All' columns show the mean of the different variables for uninsured people, NCMS and NRBMI participants, and the whole sample respectively. It is obvious that due to the presence of missing values, the number of observations is not the same in all the variables before the imputation. This problem is especially severe for Grade, Expenditure Cost, Han and Household Income. Regarding the remaining variables besides response variables, the number of gaps is very small and always below 5% of the total sample. In general, imputation increases the number of observations without having a significant impact in variables features. For this reason, imputed data are considered in the preferred analysis developed in the following sections. However, we also study the robustness of our results to this transformation.

Table 1 Statistic summary by insurance and imputation

	Before Imputation				After Imputation			
	Uninsured_b	Insured_b	All_b	#Observations_b	Uninsured_a	Insured_a	All_a	#Observations_a
Panel 1: Utilisation								
#Hospital visit in last year	1.5(0.027)	2.1(0.026)*	1.9(0.019)	32,222	1.6(0.027)	2.1(0.025)*	1.9(0.019)	32,789
#Hospital visit in last month	1.1(0.020)	1.1(0.012)	1.1(0.011)	9,198	1.1(0.02)	1.1(0.012)	1.1(0.01)	9,418
Panel 2: Health status								
#Sick in last month	0.5(0.009)	0.4(0.006)	0.4(0.005)	32,222	0.5(0.009)	0.4(0.006)*	0.4(0.005)	32,789

Self-rated health status	2.1(0.021)	2.1(0.013)	2.1(0.011)	7,535	2.1(0.021)	2.1(0.013)	2.1(0.011)	7,551
Panel 3: Independent variables								
Insurance	0 (0.000)	1(0.000)	0.7(0.003)	32,222	0(0.000)	1(0.000)	0.7(0.003)	32,789
Age	6.8(0.045)	7.8(0.029)*	7.5(0.025)	32,213	6.8(0.044)	7.8(0.029)*	7.5(0.025)	32,789
Gender [1]	0.5(0.005)	0.5(0.003)	0.5(0.003)	32,222	0.5(0.005)	0.5(0.003)	0.5(0.003)	32,789
Grade	2.1(0.010)	2.2(0.009)*	2.2(0.007)	20,404	1.7(0.008)	2(0.007)*	1.9(0.006)	32,789
Han	0.9(0.003)	0.9(0.002)*	0.9(0.002)	28,393	0.9(0.003)	0.9(0.002)*	0.9(0.002)	32,789
Height (cm)	111.7(0.334)	119.6(0.215)*	117(0.183)	30,634	110.4(0.323)	118.9(0.21)*	116(0.178)	32,789
Weight (0.5 kg)	47.4(0.273)	53.0(0.192)*	51.1(0.158)	31,296	47.7(0.267)	53.1(0.188)*	51.2(0.155)	32,789
Hukou [2]	0.8(0.004)	0.8(0.003)*	0.8(0.002)	32,148	0.8(0.004)	0.8(0.003)*	0.8(0.002)	32,789
Urban Area	0.4(0.005)	0.4(0.003)	0.4(0.003)	31,982	0.4(0.005)	0.4(0.003)	0.4(0.003)	32,789
Household Income (10M RMB)	4.3(0.061)	5.2(0.052)*	4.9(0.041)	30,436	4.3(0.057)	5.2(0.051)*	4.9(0.039)	32,789
Education Cost (10M RMB)	0.2(0.004)	0.2(0.004)*	0.2(0.003)	22,201	0.2(0.004)	0.3(0.003)*	0.3(0.003)	32,789

Standard error of mean in parentheses.
* indicates the difference between insured group and uninsured group is significant at 5% level.
Response variables are not included in the imputation model, the reason for the difference of response variables before and after imputation is due to the missingness of 'Insurance'.
[1] Gender takes value 1 for male, and takes value 0 for female.
[2] Hukou takes value 1 for agriculture hukou, and takes value 0 for non-agriculture hukou.

4. Methodology

Our purpose is to estimate the causal impact of participating in social medical insurance on health care utilisation and health status. It should be noted that unobservable Individual characteristics like risk preference and time preference could affect individuals' insurance enrolment decisions, their health care utilisations and health status. Therefore failing to control for it could result in bias estimation. For robustness, here this issue is considered under three alternative methodologies. The first estimation (FE henceforth) is based on the following regression model

$$Y_{it} = \alpha_0 + \alpha_1 INS_{it} + \alpha_2 X_{it} + T_t + \gamma_i + \gamma_p + \varepsilon_{it} , \qquad (1)$$

where Y_{it} is the response variable, either hospital visit times in last year; or hospital visit time in last month; or sick frequency in last month; or self-rated health status, in year t for individual i; INS_{it} is a dummy variable that takes value 1 if individual i took the treatment in year *t* and zero otherwise; X_{it} is a *11x1* vector including the control variables which are predisposing variables and enabling variables defined in the data section, T_t is a year fixed effect; γ_i and γ_p are individual and province fixed effects; ε_{it} is the error component and α_i, for i=0, 1 and 2 are parameters to be estimated. Our focus estimation is a_1 which explains the impact of participating in social medical insurance schemes on our response variables.

Although this strategy already controls for individual characteristics, a difference-in-difference (DID) approach is especially desirable in this context as it mimics an experimental research design by comparing the effect of treatment on a treated group versus a control group. This approach has become increasingly popular in studying the impact of insurance on health outcomes; see for example Kaestner et al. (2001) and Liu et al. (2002). DID estimation is based on the difference between the response variables for treated and control units before and after the intervention. It can be obtained from the following regression analysis. In our baseline estimation, we consider the impact of insurance between each two consecutive waves. Therefore, an individual belongs to the control group if she/he is not insured in the first wave but insured in the second wave while individuals in the control group are not insured in any of the two waves.

An alternative to this approach is propensity score matching with difference-in-difference method (PSM with DID) which is to estimate the DID regression on similar individuals from treated and control groups based on observables. PSM with DID method has been used in empirical works by, for example, Lei & Lin (2009) and Chen & Jin (2012). Similar individuals in the treated and control groups can be obtained by using different matching methods which include nearest neighbour matching, caliper matching, kernel matching, etc. We use kernel matching method because it achieves a lower variance compared to other alternatives as more information is used. Kernel matching is a non-parametric matching estimator that uses weighted averages of all individuals in the control group to construct the counterfactual outcome. Comparing to other matching methods, a kernel method does not match observations in control to any given treatment observation, but rather constructs a weighted average of all observations in the control group of the sample as a hypothetical comparison observation.[3] The weights are determined by the distance to the treatment observation: Closer comparison observations always receive larger weights (Mensah et, al., 2010). The precise nature of the weighting is determined by form of the kernel and, more importantly, its bandwidth: a larger bandwidth tends to lead to lower standard errors, but endangers the identification assumption of conditional independence (Silverman, 1986). Based on Heckcan et al. (1997) the bandwidth we choose is 0.06 which optimises the trade-off between variance and bias.

Note that, although in the PSM with DID approach treatment and control groups are chosen based on observables, this methodology remove at least any bias based on time-invariant non-observable individual characteristics.

It is noteworthy that the three approaches are defined for the linear case, however, it is easy to adjust these models for the case in which the regressions are non-linear. This is relevant because as it has been shown, the response variables take discrete values and neither of them follows a normal distribution. However, it is straightforward to adjust equation (1) to allow for a categorical dependent variable such as a logit model. Using this type of specification, it is possible to estimate the marginal effect of participating in social medical insurance schemes on children's health outcomes.

5. Results

Table 2 shows the estimated causal effects of social medical insurance on the different indicators of health care utilisation and health status of children described in the data section. The first three columns report estimations of the impact of our treatment variable for each response variable considering the FE, DID and PSM with DID approaches applied to the imputed database. The last three columns show similar results using the non-imputed database. These initial estimations do not take consideration of the discrete nature of our response variables previously discussed. However, we start with this standard approach for comparison with the previous literature(Lei & Lin, 2009; Chen & Jin, 2012; Li & Zhang, 2013).

It can be noticed that both imputed and non-imputed databases yield similar qualitatively results. Based on the fact that estimations with the imputed database are more precise due to the use of more observations, we will carry on our analysis with the imputed database. However, subsequent results in this paper are robust to the consideration of the non-imputed database.[4]

Regarding the impact of insurance on health care utilisation, all three estimations consistently show that participating in social medical insurance schemes significantly increases health care utilisation when it is observed for a long time period. More specifically, being insured increases yearly hospital visit frequency on average by a range of 0.2-0.4 times. However, its impact on monthly hospital visit frequency is not significant. Regarding health

[3] By applying nearest neighbour matching technique, one or more individuals from the control group are chosen to match a treated individual that is closest regarding propensity score. Caliper matching further imposes a tolerance level on the maximum propensity score distance. However, both of them only consider limited information of the control group.

[4] These estimations are available from the authors upon request.

status, social medical insurance schemes significantly increase sick frequency in the previous month. However, this significance is only marginal when the PSM with DID method is used. In addition to this, we could not find a significant causal effect on children's self-rated health status.

Table 2 Impact of the social medical insurance schemes on health outcomes

	Imputed			Non-Imputed		
	(1) FE	(2) DID	(3) PSM with DID	(4) FE	(5) DID	(6) PSM with DID
#Hospital visit in last year	0.219***	0.431***	0.408***	0.080	0.268**	0.299**
	(4.27)	(4.33)	(3.99)	(1.14)	(2.21)	(2.12)
R-Square	0.594	0.040	0.005	0.740	0.036	0.003
#Observations	32,789	14,450	14,444	12,661	5,169	5,220
#Hospital visit in last month	0.015	0.016	0.0004	-0.013	-0.192	-0.096
	(-0.33)	(-0.24)	(-0.01)	(-0.11)	(-1.60)	(-0.79)
R-Square	0.754	0.023	0.002	0.906	0.037	0.011
#Observations	9,418	4,162	4,162	2,725	1,179	1,115
#Sick in last month	0.016	0.061**	0.057*	-0.009	0.041	0.038
	(-1.11)	(-2.04)	(-1.84)	(-0.37)	(-0.92)	(-0.85)
R-Square	0.528	0.037	0.004	0.665	0.024	0.003
#Observations	32,789	14,450	14,444	12,661	5,169	5,220
Self-rated health status	-0.018	0.047	0.122	0.013	0.010	0.094
	(-0.44)	(0.55)	(1.16)	(0.14)	(0.07)	(0.69)
R-Square	0.734	0.013	0.005	0.899	0.020	0.004
#Observations	7,551	2,598	1,883	4,052	1,039	920

T statistics in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

As discussed before, neither of the dependent variables follows normal distribution. More specifically, all our dependent variables besides self-rated health status, take a few number of positive discrete values and zeroes while self-rated health status is measured by an ordinal 5-point scale which implies that the distance between a 1 (excellent) and 2 (very good) has the same meaning as the distance between a 4 (fair) and 5 (pool). Therefore, a proper regression analysis should not be based on a standard OLS estimation but on an alternative methodology that takes into account these data features.

According to this discussion, we split the different discrete values that the four response variables may take into ordered groups and specify a bivariate logit model for the probability to belong to each of these groups compared to the lowered order group. In particular, for hospital visit frequency in last year, the following four subgroups are defined: low hospital visit (LHV_y); fair hospital visit (FHV_y); high hospital visit (HHV_y) and higher hospital visit (HrHV_y) for individuals who went to hospital 1 , 2 , 3 and more than 3 times, respectively in last year. For example, in the LHV_y group, the response variable is a dummy variable which takes value 0 and 1 for individuals who did not go to hospital and went to hospital 1 time in last year, respectively. In the FHV_y group, the dummy response variable takes value 0 and 1 for individuals who went to hospital less than 2 times and 2 times in last year, respectively. Definitions of all the other groups are alike. Similarly, the following four subgroups are defined for hospital visit frequency in last month: low hospital visit (LHV_m); fair hospital visit (FHV_m); high hospital visit (HHV_m) and higher hospital visit (HrHV_m) for individuals who went to hospital 1 , 2 , 3 and more than 3 times, respectively in last month.

For sick frequency in last month, four subgroups are defined: low sick frequency (LSF_m); fair sick frequency (FSF_m); high sick frequency (HSF_m) and higher sick frequency (HrSF_m) for individuals who got sick 1, 2, 3 and more than 3 times, respectively. Regarding self-rated health status, we follow Simon et al. (2017) and dichotomize it into three indicators: "excellent (E)," "very good or better (VG)," and "good or better (G)," for self-rated health status values of 1, 2 and 3, respectively.

Note that as estimation results under these three proposed econometric approaches are similar, for the sake of brevity and also because it is the most accurate estimation method, we carry on the analysis only showing results under the PSM with DID approach from now on. Table 3 shows the marginal effects at mean values of PSM with DID method of each sub-group. It can be noted that social medical insurance schemes significantly increase health care utilisation in LHV_y, HHV_y and HrHV_y groups. This indicates that having insurance increases the probability of using hospitals per year by 4.3%, 2.2% and 3.6% for the LHV_y FHV_y and HrHV_y groups, respectively. This is particularly interesting as it suggests the insurance schemes not only encourage children to start using medical services, but also enable them to take more medical treatments when necessary. However, being insured does not increase the monthly hospital use in each sub-group which can be due to the fact that a significant change of health care utilisation may not be observable during such a short time period.

Regarding sick frequency, participating in the insurance schemes significantly increases sick frequency in LSF_m group. Noted this is a marginal significance and only happened in low sick frequency group which suggests that there is not strong evidence about a deterioration of health status caused by social medical insurance. This result is consistent with the aggregate analysis under the PSM with DID method reported in Table 2.

Regarding the dichotomized self-rated health status, participating in the insurance schemes does not have significant influence on the probability of reporting 'very good' or 'good'. However, we observe a significant decrease in the probability of reporting 'excellent' of 10.8% which seems to indicate that insurance only has a significant negative effect on self-rated health status for those who already have an excellent health condition. Two potential explanations for this result are either that individuals increase their health expectations after having insurance, or, that they can foresee that they would have some minor health problems which was not captured in our causal analysis before buying insurance. Interestingly this result was masked in the aggregate analysis in Table 2.

Table 3 Impact of the social medical insurance schemes on health outcomes in different heath status groups. Marginal impacts evaluated at mean values.

Variable	**(1)**	**(2)**	**(3)**	**(4)**
	LHV_y	FHV_y	HHV_y	HrHV_y
#Hospital visit in last year	0.043**	0.019	0.022*	0.036***
	(2.40)	(1.31)	(1.78)	(2.65)
Pseudo R-Square	0.002	0.002	0.002	0.004
#Observations	9,621	11,111	12,293	14,444
	LHV_m	FHV_m	HHV_m	HrHV_m
#Hospital visit in last month	0.006	0.014	-0.015	0.008
	(0.18)	(0.52)	(-1.12)	(0.63)
Pseudo R-Square	0.003	0.001	0.003	0.017
#Observations	3,166	3,847	4,063	4,162
	LSF_m	FSF_m	HSF_m	HrSF_m
#Sick in last month	0.027*	0.015	-0.002	0.005
	(1.72)	(1.50)	(-0.41)	(1.12)
Pseudo R-Square	0.001	0.002	0.003	0.018
#Observations	13,058	13,979	14,288	14,444
	E	VG	G	
Self-rated health status	-0.108**	-0.030	0.008	
	(-2.41)	(-0.57)	(0.31)	
Pseudo R-Square	0.007	0.002	0.002	
#Observations	1,883	1,883	1,883	

Z-statistics in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

It is also particularly relevant to study the differential impact of insurance schemes on high and low income families. In fact, Currie and Gruber (1996) and Kaestner et al. (2001) in their highly influential papers indicate that low income children are the main target of social insurance expansion in many countries and their corresponding health outcomes are worth investigating. As mentioned in the background section, individuals living under national poverty line (NPL) can get government subsidies to cover the entire insurance premium. Therefore, it is apparent that the Chinese government wants more financially disadvantaged children to get access to insurance schemes benefits. However, the efficiency of this affirmative action needs to be further examined.

In order to do this, we classify children into two groups and include individuals in the below-NPL and above-NPL groups depending on whether their household per capita income is less or higher than the NPL which is 2300 RMB per capita, respectively.

Table 4 presents PSM with DID estimations of the impact of social medical insurance on health outcomes of children in different income sub-groups by using an ordered logit model. Only one estimation ignoring the discrete nature of the response variables for each of the two groups is presented because, due to the small number of observations, it is impractical to perform different estimations for each of the different discrete values of the response variable. It can be seen that insurance participation significantly increases yearly hospital visit frequency in both income groups but consistently with the previous analysis no improvement for monthly hospital visit times is observed. Self-rated health status is not affected by insurance treatment in neither of the groups. However, a significantly positive impact of insurance on monthly sick frequency is observed in the estimation for the low income population. A plausible explanation for this is people could not consider minor health problems as a potential problem when they do not have the possibility to get insured. However, having insurance may make them more aware of these health problems.

Table 4 Impact of the social medical insurance schemes on health outcomes in different income groups

	(1)	(2)
	Income_above NPL	Income_below NPL
#Hospital visit in last year	0.241***	0.504***
	(3.29)	(3.07)
Pseudo R-Square	0.002	0.003
#Observations	11,843	2,601
#Hospital visit in last month	-0.027	0.219
	(-0.20)	(-0.76)
Pseudo R-Square	0.000	0.002
#Observations	3,454	708
#Sick in last month	0.070	0.617***
	(-0.82)	(-3.36)
Pseudo R-Square	0.001	0.007
#Observations	11,843	2,601
Self-rated health status	0.214	0.934
	(1.00)	(1.64)
Pseudo R-Square	0.002	0.009
#Observations	1,580	303

Z-statistics in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

Another important distinction regards to the different impact of insurance in rural and urban areas. Children's health outcomes and also the possibility of delivering a proper health treatment may vary according to their living environments, healthcare facilities and socio-economic factors. In addition to this, social medical insurance schemes of rural and urban China have different target population. Therefore, some researchers study urban insurance and rural insurance schemes separately (Li & Zhang, 2013). The estimations of ordered logit model using PSM with DID method for rural and urban areas are shown in Table 5. It can be seen that yearly hospital visit frequency are significantly improved among rural population but not among the urban population. However, no evidence is found for the improvement of monthly hospital visit, monthly sick frequency and self-rated health status of both groups after participating in the insurance scheme.

Table 5 Impact of the social medical insurance schemes on health outcomes in different geography groups

	(1)	**(2)**
	Rural	Urban
#Hospital visit in last year	0.413***	0.121
	(4.81)	(1.14)
Pseudo R-Square	0.002	0.001
#Observations	8,987	5,457
#Hospital visit in last month	-0.022	0.148
	(-0.14)	(-0.72)
Pseudo R-Square	0.002	0.002
#Observations	2,550	1,612
#Sick in last month	0.155	0.205
	(-1.60)	(-1.64)
Pseudo R-Square	0.002	0.002
#Observations	8,987	5,457
Self-rated health status	0.288	0.234
	(1.15)	(0.71)
Pseudo R-Square	0.004	0.001
#Observations	1,197	686

Z-statistics in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

Our different analyses consistently show that social medical insurances increase the use of hospitals, however, the increase of hospital use may occur either because of a better access to medical services or the increase of ill (Lei & Lin, 2009). In order to figure out this issue, we include a dummy variable for sick which takes value 1 and 0 for those who was sick and who was not sick in previous month, respectively. We check whether the effect of insurance on hospital use is different for these two groups by using propensity score matching with triple differences method (PSM with DDD).

Column (1) of Table 6 shows the PSM with DDD estimation by using ordered logit model for the aggregate analysis and followed by the marginal impacts evaluated at mean values of PSM with DDD method by using logit model for four sub-groups which are defined as in Table 3. It shows that hospital use does not vary significantly between the two groups which means better access to medical services and increase of ill are equally important to explain the increase of hospital use. This result is inconsistent with Lei & Lin (2009) who found that uninsured people accessed to hospital more when sick. However, they considered this result as unexpected which could be due to the small number of observations.

Table 6 Impact of the social medical insurance schemes on yearly hospital use in different sick groups by using triple differences method.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Variable	#Hospital visit in last year	LHV_y	FHV_y	HHV_y	HrHV_y
Insurance	-0.02	-0.031	-0.007	0.038	-0.017
	(-0.14)	(-1.04)	(-0.25)	(1.32)	(-0.86)
Pseudo R-Square	0.051	0.072	0.028	0.035	0.105
#Observations	14,444	9,621	11,111	12,293	14,444

Z-statistics in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

Our results show that individuals increase the use of hospitals when they are insured but, at the same time, it can generate in some cases a marginal deterioration on health status that requires a further analysis. Some potential explanations previously discussed regard potential endogeneity problems of the treatment variable or to the fact that insurance make people more aware of minor health problems. However, another explanation for this effect is that insurance may lead to moral hazard problems because of a reduction in future costs associated to illnesses (Ehrlich & Becker 1972; Bates et.al, 2010). Although in principle this cannot be deemed as a very important problem in our case because many risky health behaviours like smoking and drinking are not common in children population. Moreover, many aspects of their life styles are mainly decided by their parents. Despite these considerations, we explore the possibility that an insured family could have less incentives to lead a healthy live by focussing our attention on Body Mass Index (BMI) which is a common measurement of moral hazard (Simon et al., 2017). In particular, we estimate the causal impact of buying an insurance on BMI using PSM with DID method.

Given that it can be argued that the impact of BMI on health is not linear but it is only a serious concern when it surpasses the threshold of overweight, we define a dummy variable denoted by Overweight which takes value 1 and 0 depending on whether an individual's BMI is more than 25 or not and estimate the impact of insurance schemes on this variable. This is a reasonable concern as overweight is associated with various risky health behaviours which include lack of physical activity and unhealthy eating patterns (Middleman et al., 1998). Thus. Table 7 presents the results of these estimations. There is no evidence showing that participating in the insurance schemes leads to a significant increase either of BMI or overweight. This is consistent with Simon et al.(2017).

Table 7 Impact of the social medical insurance schemes on BMI and overweight

Variable	(1)	(2)
	BMI[1]	Overweight
Insurance	-0.127	0.001
	(-0.51)	(0.12)
Pseudo R-Square	0.003	0.006
#Observations	14,444	14,444

T-statistic in parenthesis in column (1) and z-statistics in parenthesis of column (2).
* p<0.1; ** p<0.05; *** p<0.01.
[I] BMI is the ratio of weight in kilograms to height in square metres.

So far our estimation results indicate that insurance has a no significant, or even negative, effect on health status. Apart from the different interpretations discussed before, an alternative explanation for this result is that insurance may need more than two years to have a positive effect. We deal with this problem considering an additional estimation based on three waves given that estimating causal effects based on two consecutive waves could be regarded as too short period for this decision to take effect on health outcomes. Therefore, individuals belonging to the treatment group in the new estimation are those who got a medical insurance in the last two waves, but did not get insurance in the first one. Control group includes individuals who did not get insurance in none of the three waves. By doing this, we are able to detect the change of health outcomes after being insured at least four years. Table 8 presents the PSM with DID estimation by using ordered logit model. It shows that participating in social medical insurance can increase the yearly hospital visit frequency in long term. However, it does not have a significant influence on monthly hospital visit frequency and health status. This new estimation is also applied to different income and geography groups.[5] All of these results agree with our previous estimations.

Table 8 Impact of social medical insurance schemes on long-term health outcomes

	(1)	(2)	(3)	(4)
	#Hospital visit in last year	#Hospital visit in last month	#Sick in last month	Self-rated health status
Insurance	0.454***	0.168	0.209	-0.232
	(3.40)	(0.65)	(1.33)	(-0.26)
Pseudo R-Square	0.002	0.002	0.009	0.003
#Observations	4,828	1,457	4,828	212

Z-statistics in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

It can be concluded from this analysis that participating in social medical insurance schemes significantly increases the access to medical services among children population which is measured by yearly hospital use. In addition to this, we find evidence of a marginal

[5] These estimations are available from the authors upon request.

deterioration of health status, however, this deterioration is not consistent with the adoption of more risky food habits. A potential explanation of this deterioration could be that individuals are inclined to have more health expectations after getting insurance.

These results are consistent with existing studies which find that social medical insurance schemes increased hospital use (Li & Zhang, 2013) while inconsistent with Lei & Lin (2009) who find that social medical insurance did not affect formal medical services. However, an important difference with our research relates to the fact that the focus here is on children's population rather than the whole population. In this respect, Chen and Jin (2012) found that there is no impact of social medical insurance on mortality rate in children population under a cross sectional database. Although mortality rate is an extreme event for children, in this case, we use a more likely event, sick frequency, to measure the health status of children.

By disaggregating our analysis into different income sub-groups, we found that social medical insurance schemes increase the yearly use of hospital in both income groups, while significantly decrease the health status among children whose family income is under NPL. It can be seen that the issue of rising health expectation is especially common among financially challenged individuals. According to Maslow's Hierarchy of Needs, only individuals who have already met the most basic needs start to think about improving their own health condition. In general, people under NPL struggle more about basic needs compared to people who above NPL. Therefore, being insured enables the poorer to consider more minor health problems.

When we disaggregate the analysis between rural and urban areas, it is found that the increase of hospital use is only significant in the former while health is unaffected by insurance. This is an interesting result as rural population is, at least in principle, more constrained in the use of health facilities.

6. Concluding remarks

Social medical insurance schemes have experienced a rapid expansion in last years. However, how these schemes work, especially for children in China, has not been an issue of great concern in the previous literature. This paper tries to fill this gap by examining the effect of social medical insurance schemes on 0-15-year-old Chinese's health care utilisation and health status.

Our results clearly indicate that health insurance exerts a positive effect on hospital utilisation especially for children living in rural areas. This is particularly relevant as children mortality rates in rural areas more than double that in urban areas (The National Bureau of Statistics of PRC, 2016a). Therefore, more hospital use in rural areas might have a positive influence in decreasing the gap of mortality rate between rural and urban China.

However, we do not find evidence of a positive impact of insurance on health status which is similar to Chen and Jin (2012). We have discussed three possible explanations for this result, namely moral hazard, the impossibility to observe the long-run effect, and the possibility that individuals become more demanding after they get the insurance. Logic and some evidence suggest that in principle the last one seems the most plausible explanation which is consistent with the important decrease of the Chinese children population during the analysis period (UNICEF, 2016). However, this paper cannot provide a completely non-speculative answer to this question. Therefore, further research, including more years of individual information and considering specific and objective information on health problems, will be necessary.

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