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Impact of supplementary private health insurance on hospitalization and physical examination in China

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Abstract

Private health insurance (PHI) is considered an important supplement to the basic social health insurance schemes in the Chinese healthcare system. However, whether the strategy of engaging PHI as supplementary coverage is effective cannot be determined without knowing the impact of supplementary PHI on healthcare access and utilization, the evidence on which is currently absent in China. Therefore, we aimed to investigate the effects of supplementary PHI on hospitalization and physical examination to provide such evidence in the Chinese setting. We conducted a cross-sectional analysis using data from the 2015 wave of China Health and Retirement Longitudinal Study (CHARLS). Using probit models and bivariate probit models with instrumental variables (IVs), we evaluated the effects of supplementary PHI on the utilization of hospitalization and physical examination. Our analyses provided evidence that supplementary PHI increased the probability of physical examination but decreased that of hospitalization. Our findings suggest that supplementary PHI in China may effectively promote the use of high-value preventive care, thereby reducing subsequent utilization of expensive medical services. The present study provided preliminary evidence that the China healthcare system can benefit from engaging PHI as supplements to SHI.

1. Introduction

The proportion of the Chinese population covered by the basic social health insurance (SHI) increased from a moderate rate of 50% to a near-universal rate of 95% during 2005–2011 (Li, Malik, & Hu, 2017; Yu, 2015). These achievements were driven collectively by three major classes of SHI schemes: Urban Employee Basic Medical Insurance (UEBMI), Urban Resident Basic Medical Insurance (URBMI), and New Cooperative Medical Scheme (NCMS) (Liu, Vortherms, & Hong, 2017; Yu, 2015). Among these, UEBMI covers formal employees in urban areas whereas URBMI and NCMS are state-subsidized voluntary programs covering urban and rural residents, respectively (Liu et al., 2017). However, the out-of-pocket (OOP) rates associated with SHI, which range from 40% to 70%, remain a major financial challenge to patients with severe illness (Luo, Bossany, Wong, & Chen, 2016; Yu, 2015; Zhang, Lei, Strauss, & Zhao, 2017). More, the state-run medical insurance fund is already running on a tight budget in the context of a continuously aging population (Ng, Dyckerhoff, & Then, 2012; Zhao & Ng, 2016), and is estimated to have an accumulated deficit of ¥735.3 billion by 2024 if countermeasures are not implemented (Chan et al., 2018; Zhao & Ng, 2016). Even more, the superficial coverage and the
inequity in benefit designs and reimbursement policies across schemes and regions create a major gap of access and utilization (Liu et al., 2017; Yu, 2015; Zhang, Tang, Zhang, Zhang, & LJPo, 2015). For example, not only the three schemes differ in the scopes of covered services and conditions, but also the financial generosity of the schemes varies substantially across regions (Liu et al., 2017; Yu, 2015). As such, the government has proposed a “multi-level health insurance system” in which SHI is supposed to secure basic healthcare need, and private health insurance (PHI) is identified as an important supplement that mainly focuses on high-cost and catastrophic inpatient care (Liu, Gao, & Rizzo, 2011). However, the uptake rate of PHI in China is still less than 4% (Yu, 2015; Zhang et al., 2017). To encourage the uptake of PHI, the government has deployed tax deduction incentives in recent years (China State Administration of Taxation. Notice of the Ministry of Finance, 2017).

The rationale of including PHI as part of the greater healthcare system is that PHI either addresses additional healthcare need by providing expanded access to otherwise uncovered services or reduces OOP burden left uninsured by the SHI policies. The former type is considered supplementary to the SHI schemes whereas the latter is considered complementary (Olivella & Vera-Hernández, 2013). The mainstream PHI policies in China, characterized by reimbursing expensive services such as hospitalization due to critical illness that are not part of SHI benefits, are considered supplementary (Chan et al., 2018; Zhao & Ng, 2016). The supplementary role of PHI in China was also empirically confirmed by Hou and Zhang who found that the expansion of SHI coverage in China did not crowd out PHI purchase, suggesting a lack of overlap in healthcare benefits (Hou & Zhang, 2017). However, little is known so far about the actual impact of the current supplementary PHI coverage on healthcare services in China, especially on relatively expensive services such as hospitalization which is what most PHI products in China target at. More, it is difficult to make assumptions about the effects of supplementary PHI in China based on evidence from other regions because the regulation of the PHI market and plans in China are not comparable to the relatively mature PHI markets. For example, discrimination based on pre-existing conditions is not prohibited in the Chinese PHI market (Chan et al., 2018). Also, PHI policies usually do not provide real-time reimbursement based on actual service costs (Luo et al., 2016). Instead, they pay a pre-determined fixed amount for a narrow set of conditions if the diagnosis and its eligibility for reimbursement are confirmed (Luo et al., 2016; Preker, Zweifel, & Schellekens, 2009). Once the one-time benefit is claimed, the renewal of enrollment becomes unlikely (Chan et al., 2018; Luo et al., 2016). Therefore, the enrollees who survive health shocks will possibly become exposed to potential future financial risks once losing the supplementary PHI coverage.

These aspects of supplementary PHI in China give rise to several theoretical concerns that are relevant to its effects. First, the absence of real-time reimbursement and the lack of affirmative information on the eligibility for reimbursement can make patients cautious about using services because there is a possibility that bills are not reimbursed subsequently. Second, the lump sum payment for a condition may reserve individual motivation to spend frugally because any remaining cash becomes the beneficiary’s wealth. Finally, because of the lack of commitment to continuous enrollment by the commercial insurers, beneficiaries may refrain from claiming the benefit if they expect catastrophic medical occurrences in the future.

A noteworthy silver lining of supplementary PHI in China is that is it not uncommon for policies to provide value-adding preventive care such as physical examination (Chan et al., 2018), likely motivated by the same cost-minimization rationale as the insurance policies in other countries – to reduce subsequent bills by preventing diseases from happening or gravitating. Consequently, supplementary PHI potentially promotes preventive care use. However, it is also reasonable to expect that insurers only encourage the use of preventive care that will offset the paid amount by the insurers themselves, such as hospitalization due to relatively severe conditions.

These complexities put together, the effects of supplementary PHI in China needs to be evidenced empirically to inform the decision-making of the government, the insurers, and possibly even the individual consumers. To insight into such, the present study was conducted to examine the effects of supplementary PHI on the use of inpatient care and preventive care. To our knowledge, the present study represents the first attempt to empirically answer such questions in the setting of China. Our analyses provided evidence that supplementary PHI in China significantly increased the probability of preventive care but decreased that of inpatient admission. Such results indicated that individuals covered by supplementary PHI experienced improved access to preventive care, which might in turn reduce hospitalization. This might be a result of an on-purpose benefit design from the insurers’ end.

The remaining of the paper proceeds as follows. Section 2 gives a review of the literature related to the incentive effects (or lack thereof) of supplementary PHI. Section 3 lays out the theoretical background of insurance effects. Section 4 describes the data and elaborates on the econometric framework used for analyses. Section 5 lists the results of the main analyses and the tests of the identifying assumptions. Section 6 provides a discussion of the results and their implications, following which was a summary of study limitations in Section 7. Section 8 concludes the paper.

2. Review of related literature

Whereas the impact of primary insurance on healthcare use has been studied abundantly in numerous countries, such impact of supplementary coverage was investigated less frequently. The literature of the effects of voluntary commercial supplements to the publicly funded Medicare in the US is relatively saturated. Wolfe and Goddeeris (Wolfe & Goddeeris, 1991) examined data from the 1970s and found that Medicare beneficiaries having supplementary PHI had higher expenditures on hospital and physician services. Also, Coulsin et al. (Coulsin, Terza, Neslusan, & Stuart, 1995) found that having Medicare supplements increased the number of prescription fills using 1990 Pennsylvanian data. Consistent with the previous results, Khandker et al. (Khandker & McCormack, 1999) and Atherly (Atherly, 2002) showed strong positive effects of Medicare supplements on total healthcare expenditures. More recently, Keane and Stavrunkova (Keane & Stavrunkova, 2016) provided new evidence that Medicare supplements increased healthcare expenditure. Focusing on the probability instead of the intensity of healthcare use, Christensen and Shinole (Christensen & Shinogle, 1997) found that Medicare supplements increased the probability of hospitalization using the 1994 National Health Interview Survey.
data. Their findings were confirmed by Dardanoni and Donni (Dardanoni & Donni, 2012) using the 2006 Health and Retirement Study data. Overall, the incentive effects of Medicare supplements on healthcare utilization were consistent in numerous studies across different periods.

Outside of the US, the effects of supplementary PHI have been documented in only a handful of studies. In France, it has been shown that supplementary PHI significantly increased physician visits (Buchmuller, Couffinhal, Grignon, & Perronm, 2004). However, an analysis in Belgium where the supplementary PHI mainly targeted at hospitalization costs showed that the supplementary PHI did not impact the number of hospitalization and even decreased the number of nights per hospitalization (Schokaert, Van Oorti, De Graeve, Lecluyse, & Van de Voorde, 2010). Using the Korean Income and Labor Survey data, Kang et al. (Kang, You, Kwon, & Oh, 2009) did not find any impact of supplementary PHI on the frequency of outpatient visits in South Korea. In line with the findings by Kang et al., Jeon and Kwon (Jeon & Kwon, 2013) did not find any effects of supplementary PHI on the number of outpatient visits using Korean Health Panel Survey data as well. However, they did find significant incentive effects of supplementary PHI on the probabilities of using outpatient services and hospitalization.

To our knowledge, the impact of supplementary PHI on preventive care was only investigated in one prior study in the literature. Menezes-Filho and Politi (Menezes-Filho & Politi, 2012) showed that Brazilians who had supplementary PHI had a higher probability of incurring preventive care including Pap test and mammogram. In contrast, the use of non-preventive healthcare services was not impacted by supplementary PHI. The analysis of supplementary PHI in Brazil has important implications for China because Brazilians are similar to Chinese in the sense that they have universal public coverage which only accounts for less than 50% of total healthcare expenditure in the country (Menezes-Filho & Politi, 2012). To date, studies on the association of health insurance with preventive care predominantly focused on primary coverage. The Oregon Health Insurance Experiment (OHIE) offered a unique opportunity to examine the effects of primary coverage on preventive care because a group of previously uninsured individuals on the Medicaid waiting list of Oregon were randomly selected to skip the list (Wallace & Sommers, 2016). Being insured was found to increase preventive care use including cholesterol tests, blood tests for diabetes, mammograms, and Pap tests in OHIE (Finkelstein et al., 2012). The 2006 Massachusetts health reform represented another extensively exploited experiment (Wallace & Sommers, 2016). When compared with nearby New England states, residents of post-reform Massachusetts had higher rates of Pat tests and vaccination (Miller, 2012; Sabik & Bradley, 2016). The Massachusetts health reform was also documented to increase preventive care use that eventually decreased preventable hospitalization (Kolstad & Kowalski, 2012). This is particularly of interest to the examination of supplementary PHI in China given the motivation of the latter to offer preventive care. More recently, the Affordable Care Act (ACA) led to changes in two tracks of primary coverage in the US. First, the ACA required all states to expand Medicaid to adults whose income was less than 138% of the federal poverty line (FPL). Although the Supreme Court ruled in 2012 that individual states can opt out of the expansion, thirty-one states still enacted the ACA requirement (Lindrooth, Perraillon, Hardy, & Tung, 2018). The ACA also mandated Medicaid policies in all states to offer a bundle of preventive services at no cost to beneficiaries (Simon, Soni, & Cawley, 2017). Such changes to Medicaid had positive effects on HIV tests but not flu shots and cancer screening (Simon et al., 2017). Second, the ACA mandate of providing preventive care without copayment applied not only to public insurance such as Medicaid but also to all primary PHI policies in the US (Lipton & Decker, 2015). This has been shown to have increased HPV test among those who were primarily commercially insured (Lipton & Decker, 2015). Whereas the findings on the effects of primary coverage are enlightening in that they are consistent with one’s expectation of the utility of insurance, they are not necessarily replicable in the analysis of supplemental coverage. To illustrate, the private insurers engage in the objective function of maximizing profit using the benefit design when they provide preventive care, yet it is rational to think that the preventive services mandated by the US government as described in the foregoing studies were devised to maximize either population health or total social welfare. Hence, the spectrum, intensity, and quality of the preventive care provided by primary insurance may be different from that of supplementary PHI.

The effects of supplementary PHI heavily depend on institutional settings. Especially, the Chinese PHI market is different from the PHI markets in the western countries for the reasons mentioned in the introduction section. In addition, to what extent the basic health insurance addresses healthcare need can affect the behavior of supplementary PHI enrollees (Boone, 2018). Hence, we aimed to obtain evidence that is specific to the supplementary PHI plans in China.

3. Theoretical background

In general, beneficiaries may increase the use of contracted healthcare services through three mechanisms, namely moral hazard, income transfer effect, and risk reduction effect (Andrew, Xander, & Eddy Van, 2006). Moral hazard, or price effect, means the level of consumption is higher when insurance reduces the costs to the beneficiaries (Andrew et al., 2006; Boone, 2015). Two distinct types of moral hazard are ex-ante moral hazard and ex-post moral hazard. The former means beneficiaries refrain from risky health behavior to a lesser extent before realized medical occurrences as a result of feeling financially protected and the latter means they utilize more services given a specific level of health risk (Pierre, 2016). Income transfer effect, or access effect, refers to the mechanism that insurance creates an ex-post transfer of income that makes certain services accessible to the beneficiaries but not so otherwise (Andrew et al., 2006). It has been argued that the utilization due to income effect is actually an “efficient moral hazard” because the resources are turned into improved health instead of being wasted (Boone, 2015). The final mechanism relates to the situation that the level of utilization is inversely proportional to financial uncertainty an individual faces, a behavior named risk reduction effect (Andrew et al., 2006). The three mechanisms are collectively termed insurance effect. The services enveloped into the benefits package are expected to be used more both on the intensive margin and the extensive margin due to the joint force of the three mechanisms.

The profit the insurers make is the difference between the premium they collect and the healthcare expenditure they pay for the
beneficiaries. To that end, insurers can optimize benefit design for their interest such that the beneficiaries choose low-cost and high-value preventive care which reduces the overall hospitalization rate. Compared with simply increasing premiums for profit, optimizing benefit design is a more reasonable strategy because it reduces operating costs of insurers that further turns into lower premiums, thereby becoming more appealing to insurance shoppers. Such a benefit design incentivizes beneficiaries to pick up more ex-post moral hazard concerning preventive care but in effect reduces ex-ante moral hazard related to hospitalization. However, such information is unknown to researchers a priori. Hence, we follow the general theory of insurance effect and hypothesize that those who had supplementary PHI incurred higher probabilities of both hospitalization and physical examination.

When analyzing the impact of supplementary PHI, it is important to isolate the insurance effect from the selection effect (Dardanoni & Donni, 2012; Keane & Stavrunova, 2016). The selection effect can arise from either adverse selection or advantageous selection. Adverse selection refers to the situation when the high-risk individuals are more likely to purchase insurance, the contrast of which is called advantageous selection (Fang, Keane, & Silverman, 2008). The supplementary PHI markets around the world have been mostly characterized by either advantageous selection or absence of self-selection (Buchmueller, Fiebig, Jones, & Savage, 2013; Fang et al., 2008; Paccagnella, Rebba, & Weber, 2013; Shmueli, 2001). Affirmative information on the direction of self-selection can help researchers to determine whether and to what extent the analysis may be affected by omitted variable bias. Without solid evidence on such, we consider it necessary to test and control potential endogeneity in the present analysis.

4. Econometric methods

4.1. Data

The present study was a cross-sectional analysis using data from the 2015 wave of the China Health and Retirement Longitudinal Study (CHARLS). CHARLS is an aging survey of 45 years and older Chinese and their spouses that used a multistage probability sampling to allow nationally representative estimates (Liu et al., 2016; Zhang et al., 2017; Zhao, Hu, Smith, Strauss, & Yang, 2012). The data from the 2015 wave included 20,284 respondents with positive cross-sectional weights. The types of information that the survey collected were 1) socioeconomic information including age, sex, education, residence (rural or urban), assets, income, working status, pension, and health insurance status; 2) health information including self-reported general health, thirteen physician-diagnosed chronic conditions, memory problem, past-year hospitalization, past-month outpatient visit, and the time of last physical examination if any (past-year preventive care use can be created using timestamp); and 3) behavioral questions including smoking status and alcohol ingestion frequency. More information on CHARLS has been described elsewhere (Chien, Lin, Phillips, Wilkens, & Lee, 2017; Zhao et al., 2012). To investigate the properties of PHI as supplementary insurance, we used the subsample that had SHI coverage in this analysis.

4.2. Empirical framework

We examined the effects of supplementary PHI on both hospitalization and physical examination. The latter was analyzed as a proxy for preventive care. We illustrated our analysis using hospitalization, but the analysis of physical examination followed the same framework. The latent variable that determines if an individual is hospitalized is

$$H_i^* = \alpha_0 + \alpha_1 PHI_i + X'_i \alpha_2 + \epsilon_i,$$

where $X_i$ is the matrix of controlled variables. Our observation is

$$H_i = \begin{cases} 1 & \text{if } H_i^* > 0, \\ 0 & \text{if } H_i^* \leq 0, \end{cases}$$

where $H_i$ is an indicator of past-year hospitalization. The general equation we are interested in estimating is therefore

$$\Pr(H_i = 1) = \Pr(H_i^* > 0) = g(\alpha_0 + \alpha_1 PHI_i + X'_i \alpha_2).$$  \hspace{1cm} (1)$$

where $\Pr()$ is the probability of the event in the parentheses. To examine the effect of supplementary PHI on the probability of hospitalization, we first conducted a probit regression that takes the form:

$$\Phi^{-1}[\Pr(H_i = 1 | PHI_i, X_i)] = \alpha_0 + \alpha_1 PHI_i + X'_i \alpha_2$$  \hspace{1cm} (2)$$

where $\Phi^{-1}$ is the probit link function. In this multivariate probit regression, $X_i$ represented 1) basic demographic information including age, sex and whether living in a rural area; 2) health condition information including the self-reported general health variable and indicators of thirteen chronic diseases; 3) socioeconomic information including total wealth (in ¥1000), annual income (in ¥1000) and education level (an indicator for high school or above); 4) risky health behavior including smoking and alcohol ingestion frequency (daily or more often); and 5) SHI types. The self-reported general health question had five categories (1 excellent, 2 very good, 3 good, 4 fair, 5 poor). When conducting regressions, we created a general health indicator (GHI) variable for fair or better health status because the median category was fair. Two variables used to denote the SHI types were an indicator for UEBMI and an indicator for NCMS. Having SHI types other than UEBMI and NCMS was the baseline category. It should be noted that the percentages of all SHI categories added up to a bit over 100% but not exactly 100% since the survey itself did not force respondents to check only one option. The coefficients of the probit regression cannot be interpreted straightforwardly. Hence, we present the
The identifying assumption of the probit regression was that PHI was uncorrelated with $\epsilon_i$. However, $\alpha_1$ in Eq. (2) would be potentially subject to two sources of endogeneity that may cause violation of this assumption and falsification of causal inference. First, there could be reverse causality between having supplementary PHI and hospitalization in a cross-sectional study because the temporal sequence was unclear in the survey. Second, individuals might have self-selected into supplementary PHI based on factors unobserved to researchers, which renders the estimates vulnerable to omitted variable bias if the unobserved factors also correlated with the outcome. To address the endogeneity issue, we additionally used an instrumental variable (IV) method to estimate the effect of supplementary PHI. IVs are exogenous variables that correlate with the potentially endogenous treatment variable (PHI in this study) but not $\epsilon_i$ (Greene, 2003). This is equivalent to saying the IVs should correlate with the outcome only through correlating with the endogenous variable. It should be noted that the exogeneity of IV only requires $\text{Cov}(IV, \epsilon_i) = 0$ (Wooldridge, 2010), and $\epsilon_i$ is already net of the association between all covariates and the outcome. In other words, it suffices that $E(\epsilon_i | IV, X_i) = 0$ for the exogeneity of the IVs to hold. The IVs we chose were an indicator of whether the respondent had any commercial pension and the attitude and financial literacy. The second IV might correlate with the endogenous variable through insurers’ advertising effort and consumption externality such as bandwagon effect (Aizawa & Kim, 2018; Huang & Tzeng, 2008). Furthermore, both the response variables of interest (past-year hospitalization and past-year physical examination) and the potentially endogenous treatment variable (PHI in this study) but not $\epsilon_i$ (Greene, 2003). This is equivalent to saying the IVs should correlate with the outcome only through correlating with the endogenous variable. It should be noted that the exogeneity of IV only requires $\text{Cov}(IV, \epsilon_i) = 0$ (Wooldridge, 2010), and $\epsilon_i$ is already net of the association between all covariates and the outcome. In other words, it suffices that $E(\epsilon_i | IV, X_i) = 0$ for the exogeneity of the IVs to hold. The IVs we chose were an indicator of whether the respondent had any commercial pension and the community-level diffusion rate of supplementary PHI not counting in the respondent for which the variable is generated. Specifically, the diffusion rate for the ith individual, $DR_i$, in a community with n respondents is calculated as

$$DR_i = \frac{\sum_{k=1}^{n} PHI_{k,i+1} - PHI_i}{n-1}$$

(5)

where $k$ denotes the kth individual in $\{1, 2, 3...i-1, i + 1... n\}$. The first IV could relate to having supplementary PHI through risk attitude and financial literacy. The second IV might correlate with the endogenous variable through insurers’ advertising effort and consumption externality such as bandwagon effect (Aizawa & Kim, 2018; Huang & Tzeng, 2008). Furthermore, both the response variables of interest (past-year hospitalization and past-year physical examination) and the potentially endogenous treatment variable (PHI) were dichotomous outcomes. Studies in the econometric literature have shown that the conventional two-stage least squares (2SLS) procedure of implementing IV leads to misspecification of the second stage and is more vulnerable to bias than bivariate probit (BVP) models when both the response variable and the endogenous variable are dichotomous (Bhattacharya, Goldman, & McCaffrey, 2006; Chiburis, Das, & Lokshin, 2012; Freedman & Sekhon, 2010). Therefore, we used the BVP approach to implement the IV analysis. The structure of the BVP model takes the following form (Greene, 2003):

$$H_i = \{X_i^\prime \beta + \epsilon_i, \epsilon_i > 0\},$$

$$PHI_i = \{X_i^\prime \phi + \epsilon_i, \epsilon_i > 0\},$$

$$\begin{bmatrix}
    \epsilon_i \\
    \epsilon_i
\end{bmatrix}
\sim \text{BVN}
\begin{bmatrix}
    \begin{pmatrix} 0 & \rho \\ \rho & 1 \end{pmatrix} & 1 \\
    1 & 1
\end{bmatrix},$$

(6)

where $1[\cdot]$ is an indicator function that equals one if the condition in the brackets is true and zero otherwise, and $\text{BVN}$ represents a bivariate normal distribution. Conditional on the IVs are valid, $\rho$ tests the exogeneity of PHI in the analyses of hospitalization and physical examination. Similar to the probit models, we present the marginal and incremental effects which were calculated using Eqs. (3) and (4). The identifying assumptions of the bivariate probit model were that the IVs were strong predictors of PHI and were exogenous to the outcomes. To test the non-weakness of the IVs, we conducted a side-track linear probability model of PHI on the IVs. The Staiger-Stock rule of thumb is that the F-statistic of regressing the endogenous variable on non-weak IVs using a linear model should be greater than 10 (Staiger & Stock, 1994). In addition, we conducted a 2SLS regression alongside the BVP model. Although the effects estimates using 2SLS were more vulnerable to bias than the BVP estimates, we still relied on the 2SLS for two tests to verify the identifying assumptions since there are no equivalent tests in non-linear IV models. First, a Cragg-Donald Wald F statistic was obtained for a weak identification test following the 2SLS. The rationale of this test is that the IV estimate is always biased but weak IVs generate bias that is as great as or even greater than an ordinary least squares (OLS) estimate, and the Cragg-Donald Wald F statistic needs to be greater than a certain critical value to limit the bias of the IV estimate within a level that is acceptable (Baum, Schaffer, & Stillman, 2007). Second, the over-identification test was used to examine the exogeneity of the IVs. Rejection of the null hypothesis of the over-identification test means at least one IV was not exogenous (Cameron & Trivedi, 2009). All analyses incorporated respondent sampling weights and were carried out using Stata (version 15; Stata Corp, College Station, TX, USA).
Table 1
Characteristics and descriptive comparison of hospitalization and physical examination of individuals having SHI with and without PHI in CHARLS.

| Characteristic                                      | With PHI (3.2%) | Without PHI (96.8%) | Total | p-Value |
|-----------------------------------------------------|-----------------|---------------------|-------|---------|
| Age (years)                                         | 53.8 (7.6)      | 60.1 (10.9)         | 59.9 (10.9) | < 0.001 |
| Male (%)                                            | 50.4            | 47.6                | 47.7  | 0.462   |
| Rural (%)                                           | 30.2            | 52.5                | 51.8  | < 0.001 |
| Mean number of chronic conditions                   | 1.62 (1.47)     | 1.77 (1.67)         | 1.76 (1.66) | 0.243   |
| Self-reported health status (%)                     | 1.29            | 1.26                | 1.29  |         |
| Excellent                                           | 2.30            | 1.26                | 1.29  |         |
| Very good                                           | 15.9            | 11.7                | 11.8  |         |
| Good                                                | 15.8            | 12.8                | 12.9  |         |
| Fair                                                | 56.5            | 54.6                | 54.6  |         |
| Poor                                                | 9.55            | 19.7                | 19.4  |         |
| Total wealth (2015 Chinese ¥)                       | 570,057 (711,521) | 455,544 (2,848,516) | 459,265 (2,798,020) | 0.112   |
| Income (2015 Chinese ¥)                             | 20,695 (59,582) | 6165 (17,864)       | 6622 (21,064) | 0.001   |
| 1-year inpatient costs (2015 Chinese ¥)             | 2463 (12,742)   | 1900 (9855)         | 1918 (9977) | 0.516   |
| Having UEBMI (%)                                    | 35.8            | 19.8                | 20.3  | < 0.001 |
| Having NCMS (%)                                     | 53.4            | 71.7                | 71.2  | < 0.001 |
| Having SHI other than UEBMI and NCMS (%)            | 13.0            | 9.45                | 9.56  | 0.062   |
| Had any past-month outpatient visit (%)             | 21.3            | 19.2                | 19.2  | 0.628   |
| Had any past-year hospitalization (%)               | 11.9            | 13.2                | 13.1  | 0.468   |
| Had any past-year physical examination (%)          | 46.1            | 31.0                | 31.5  | < 0.001 |

Results are presented as mean (standard deviation) unless otherwise specified. Abbreviations: PHI, private health insurance; SHI, social health insurance; UEBMI, urban employee basic medical insurance; NCMS, new cooperative medical scheme.

a The percentages incorporated sampling weights. Therefore, the actual sample sizes in each group were not reported because they did not correspond to the reported percentages.

b The number of non-missing responses was 17,401.

c The number of non-missing responses was 17,454.

d The number of non-missing responses was 17,703.

5. Results

We identified 17,703 respondents (87.3% of the 2015 samples) who had SHI in the 2015 cross-sectional data. Of those who had any SHI, 493 individuals also had supplementary PHI. When sampling weights were incorporated, 3.2% of those who had SHI also had supplementary PHI. The descriptive statistics of the analytical sample are presented in Table 1. Those who had supplementary PHI were significantly younger (mean: 53.8 vs 60.1 years, \( p < .001 \)), less likely to live in rural areas (30.2% vs 52.5%, \( p < .001 \)), and less likely to be in poor self-reported health status (9.6% vs 19.7%, \( p < .001 \)). The proportions of males (50.4% vs 47.6%, \( p = .462 \)) were not statistically different across the two groups, neither were the number of chronic conditions (mean: 1.62 vs 1.77, \( p = .243 \)) and total wealth (mean: ¥570,057 vs ¥455,544, \( p = .112 \)). Also, PHI beneficiaries had significantly higher annual income (mean: ¥20,695 vs ¥6165, \( p = .001 \)), were more likely to have UEBMI (35.78% vs 19.78%, \( p < .001 \)) and were less likely to have NCMS (35.35% vs 71.73%, \( p < .001 \)). More, the two groups had similar rates of coverage by SHI other than UEBMI and NCMS (13.0% vs 9.45%, \( p = .062 \)). Even more, those who had supplementary PHI had similar rates of past-month outpatient visit (21.3% vs 19.2%, \( p = .628 \)) and past-year hospitalization (11.9% vs 13.2%, \( p = .468 \)) as those without supplementary PHI but a higher rate of past-year physical examination rate (46.1% vs 31.0%, \( p < .001 \)) than those without supplementary PHI. The descriptive statistics suggested that the two groups had systematic differences in some observable characteristics.

The estimates of the impact of supplementary PHI on the probability of hospitalization are presented in Table 2. According to the estimate of the incremental effect using the probit model, supplementary PHI was insignificantly associated with a 0.0428 (SE: 0.0304) lower probability of hospitalization. However, supplementary PHI significantly decreased the probability of hospitalization by 0.300 (SE: 0.0744) using the BVP estimates. In addition, the \( \rho \)-value of the correlation between the error terms in the BVP was 0.227, suggesting endogeneity of supplementary PHI in the analysis of hospitalization. More, the \( \rho \)-value of the over-identification test of IVs was 0.562, following which we could not reject the null hypothesis that the IVs were exogenous in the analysis of hospitalization.

The results of the analyses related to the non-weakness of IVs are presented in Table 3. The first-stage F-statistic was 23.28, which was greater than the Staiger-Stock rule of thumb. Also, the Cragg-Donald Wald F statistic for weak identification test was 86.47 in the analysis of hospitalization and 87.01 in the analysis of physical examination, each of which was greater than the critical value (19.93) to consider the IVs non-weak. These results suggested that the IVs had a sufficiently strong association with having supplementary PHI. The results of the over-identification test in the analysis of hospitalization and the non-weakness tests in 2SLS favored the identifying assumptions of the BVP model in the present analysis, thereby nullifying the identifying assumption of the probit model for the analysis of hospitalization because \( \rho \) was statistically significant in the BVP model.

The results of PHI choice equations in the BVPs (the counterparts of first-stage equations in 2SLS) are also presented. Table 4 contains the choice equation estimates from the BVPs of both outcomes. There were two sets of estimates because the sample sizes of the two analyses were slightly different due to missing values. According to the results in Table 4, both IVs significantly predicted PHI.
## Table 2
Probit and bivariate probit regression results of hospitalization on having PHI.

|                                | Probit$^a$ | Bivariate probit$^a$ |
|--------------------------------|------------|----------------------|
| **Having PHI**                 | −0.0428    | −0.300$^{***}$       |
|                                | (0.0304)   | (0.0744)             |
| **Age**                        | 0.00137$^*$| 0.0135               |
|                                | (0.000563) | (0.000566)           |
| **Male**                       | 0.0351$^*$ | 0.0349$^*$           |
|                                | (0.0111)   | (0.0113)             |
| **Living in the rural area**   | −0.00517   | −0.00786             |
|                                | (0.0105)   | (0.0108)             |
| **Self-reported health fair or above** | −0.103$^{***}$ | −0.104$^{***}$       |
|                                | (0.0101)   | (0.0102)             |
| **Ever had condition**         |            |                      |
| **High blood pressure**        | 0.0106     | 0.0106               |
|                                | (0.00944)  | (0.00956)            |
| **Diabetes**                   | 0.0482$^{**}$ | 0.0480$^{***}$       |
|                                | (0.0141)   | (0.0143)             |
| **Cancer**                     | 0.0615$^*$ | 0.0610$^*$           |
|                                | (0.0302)   | (0.0307)             |
| **Lung disease**               | 0.0498$^{***}$ | 0.0511$^{***}$       |
|                                | (0.0133)   | (0.0137)             |
| **Heart problem**              | 0.0515$^{**}$ | 0.0527$^{***}$       |
|                                | (0.0108)   | (0.0110)             |
| **Stroke**                     | 0.00795    | 0.00867              |
|                                | (0.0243)   | (0.0249)             |
| **Psychiatric problem**        | −0.00581   | −0.00528             |
|                                | (0.0303)   | (0.0310)             |
| **Arthritis**                  | −0.00251   | −0.00181             |
|                                | (0.00905)  | (0.00913)            |
| **Dyslipidemia**               | 0.0386$^*$ | 0.0404$^{***}$       |
|                                | (0.0118)   | (0.0119)             |
| **Liver disease**              | 0.0268     | 0.0285               |
|                                | (0.0192)   | (0.0194)             |
| **Kidney disease**             | 0.0262     | 0.0255               |
|                                | (0.0137)   | (0.0139)             |
| **Stomach/digestive disease**  | 0.0157     | 0.0156               |
|                                | (0.00961)  | (0.00971)            |
| **Asthma**                     | 0.00819    | 0.00651              |
|                                | (0.0192)   | (0.0197)             |
| **Memory problem**             | 0.0427     | 0.0412               |
|                                | (0.0310)   | (0.0315)             |
| **Household total wealth (in thousand Chinese ¥)** | −0.00000173 | −0.00000158 |
|                                | (0.00000250) | (0.00000240) |
| **Annual personal income (in thousand Chinese ¥)** | −0.00236$^{**}$ | −0.00236 |
|                                | (0.000521) | (0.000516)           |
| **Education high school or above** | −0.00837 | −0.00513 |
|                                | (0.0145)   | (0.0144)             |
| **Smoke now**                  | −0.0383$^{**}$ | −0.0384$^*$         |
|                                | (0.0126)   | (0.0127)             |
| **Drink alcohol daily or more often** | −0.0270 | −0.0283 |
|                                | (0.0146)   | (0.0146)             |
| **Have UEBMI$^b$**             | 0.00755    | 0.00899              |
|                                | (0.0180)   | (0.0178)             |
| **Have NCMS$^b$**              | −0.0118    | −0.0149              |
|                                | (0.0170)   | (0.0168)             |
| **p-value of the correlation between error terms (p)** | NA        | 0.027                 |
| **p-value of over-identification test using 2SLS** | NA        | 0.562                 |
| **N**                          | 6768       | 6765                 |

Standard errors in parentheses.
Abbreviations: PHI, private health insurance; UEBMI, urban employee basic medical insurance; NCMS, new cooperative medical scheme; NA, not applicable; 2SLS, two-stage least squares.

$^a$ Results are presented as average marginal effects or incremental effects (standard error) unless otherwise specified.

$^b$ The category of social health insurance other than UEBMI and NCMS was left out in regressions.

* $p < .05$.

** $p < .01$.

*** $p < .001$. 

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The development of supplementary PHI. Nevertheless, supplementary PHI in China does have the potential to curb healthcare costs, access concerns, keeping the commercial insurers’ budget in check may not be part of the government’s original motive to encourage whether supplementary PHI can also improve access to expensive healthcare services uncovered by the basic schemes, we did provide to nuance in the test results.

Weak IVs, then the Cragg-Donald Wald F-statistic should be at least 19.93. Instruments that will lead to a rejection rate of \( r \) (e.g. 10%) when the true rejection rate is 5%. Specifically, if our tolerated \( r \) is 10% for IVs to be non-weak IVs, then the Cragg-Donald Wald F-statistic should be at least 19.93.

Table 3

**Weak instrumental variable tests.**

| Statistic | Outcome | Value | Rule of thumb value | References |
|-----------|---------|-------|---------------------|------------|
| F-statistic of first-stage linear probability model | Both outcomes | 23.28 | At least 10 for non-weak IV | (Staiger & Stock, 1994) |
| Cragg-Donald Wald F statistic for weak identification test* | Hospitalization | 86.47 | Stock-Yogo weak identification test critical value for 10% maximal IV size is 19.93b | (Baum et al., 2007) |
| | Physical examination | 87.01 | |

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coverage. Also, the estimates across the two BVP models were close to each other although there was nuance in magnitudes.

Table 5 lists the results of regressing physical examination on having supplementary PHI. According to the results of both the probit model 0.190 (SE: 0.0538) and the BVP model 0.646 (SE: 0.158), supplementary PHI significantly increased the probability of having any physical examination. In addition, the \( p \)-value of \( p \) was 0.037, indicating potential endogeneity of supplementary PHI. More, the \( p \)-value of the over-identification test was 0.283, failing the rejection of IV exogeneity. As such, the identifying assumptions of the IV analyses were statistically valid in the physical examination BVP model whereas the probit regression likely generated biased and inconsistent estimates, although the probit and the BVP results had the same direction.

**6. Discussion**

Using IV methods to account for endogeneity in the analysis of CHARLS data, we identified a negative impact of supplementary PHI on the probability of hospitalization and a positive impact on the probability of physical examination. To our knowledge, the present study is the first in the literature to examine the impact of supplementary PHI in China.

Hospitalization is the main type of financial risk that supplementary PHI in China aims to offset. As such, it is directly relevant as an outcome to the analysis of the effects of supplementary PHI in China. Physical examination, on the other hand, was considered a proxy for preventive care in our analysis. There were other types of proxies for preventive care services used in literature such as Pap test and cancer screening. However, the information in CHARLS lacked the granularity to use such proxies. To the extent that physical examination is a valid proxy of preventive care, the present findings suggested that supplementary PHI in China improved access to preventive care. In contrast to our hypothesis, the results suggested that supplementary PHI reduced the probability of hospitalization. It should be noted that this did not necessarily indicate deteriorated access to inpatient services associated with supplementary PHI since this would be highly counterintuitive. Even in the worst scenario of an absence of utility attached to supplementary PHI, the enrollees can simply opt out of claiming the benefit. Hence, a more sensible interpretation is that the preventive care use brought about by supplementary PHI was “efficient moral hazard”. That is, the increased use of preventive care represents improved access to risk-reducing services and discouraged risky behavior that may eventually lead to hospitalization.

These properties of supplementary PHI in China coincide with the popular and cutting-edge practice of value-based insurance design (VBID) in the US. The VBID among the US managed care organizations is used to incentivize the uptake of high-value care which improves health outcomes and reduces aggregate costs (Pauly & Blavin, 2007; Rajender, Ashutosh, & Mark, 2018; Yeung, Basu, Marcum, Watkins, & Sullivan, 2017). In such health insurance policies, the insurers devise the benefits package to align individual moral hazard with the increased use of targeted services that result in decreased expensive medical occurrences, which is an effective strategy to improve health outcomes and containing costs (Rajender et al., 2018). Leveraging preventive care to reduce the likelihood of developing severe medical conditions that may lead to hospitalization mirrors such a framework. However, it remains unclear to what extent the insurers manipulated the design of such policies since there was generally a lack of interaction between commercial insurers and healthcare providers in China (Chan et al., 2018). Knowing exactly which types of preventive care are offered by supplementary PHI policies can also enable researchers to examine the potential cost-saving benefit design with greater details. However, there are numerous insurers offering various policies to individuals with heterogeneous risk preferences in different regions of China. Hence, it is difficult to summarize the coverage of preventive care by supplementary PHI since information in either survey data or other sources does not usually collect information that is detailed enough. Future studies that systematically survey such information and quantitatively characterize this aspect of all PHI policies in China can greatly facilitate the research in this area.

Our findings have important potential implications for healthcare financing and supplementary PHI regulation in China. The strategy of the Chinese government was to encourage supplementary PHI to address the unmet healthcare need left by basic insurance schemes (Liu et al., 2011). To that end, the government deployed tax incentives to encourage the uptake of PHI (China State Administration of Taxation. Notice of the Ministry of Finance, 2017). Based on the current results, the supplementary PHI in China at least partially increased access to high-value preventive healthcare in China. Whereas our findings did not provide direct evidence on whether supplementary PHI can also improve access to expensive healthcare services uncovered by the basic schemes, we did provide evidence that supplementary PHI contributes to reducing hospitalization through offering appropriate preventive services. Unlike access concerns, keeping the commercial insurers’ budget in check may not be part of the government’s original motive to encourage the development of supplementary PHI. Nevertheless, supplementary PHI in China does have the potential to curb healthcare costs,
Table 4
Results of PHI choice equations in the BVPs.

| Variable                                                                 | PHI choice equation in the hospitalization BVP model | PHI choice equation in the physical examination BVP model |
|---------------------------------------------------------------------------|-----------------------------------------------------|----------------------------------------------------------|
| IV - commercial pension indicator                                         | 0.0619***                                           | 0.0546***                                                |
| (0.0173)                                                                  | (0.0167)                                             |
| IV - community-level diffusion rate of supplementary PHI                  | 0.280***                                            | 0.305***                                                 |
| (0.0945)                                                                  | (0.0902)                                             |
| Age                                                                       | −0.00144***                                          | −0.00153***                                              |
| (0.000346)                                                                | (0.000359)                                           |
| Male                                                                      | −0.000426                                           | 0.000883                                                 |
| (0.00729)                                                                 | (0.00770)                                            |
| Living in the rural area                                                  | −0.00811                                            | −0.00728                                                 |
| (0.00639)                                                                 | (0.00618)                                            |
| Self-reported health fair or above                                         | 0.0140†                                             | 0.0152†                                                  |
| (0.00693)                                                                 | (0.00693)                                            |
| Ever had condition                                                        |                                                     |                                                         |
| High blood pressure                                                       | 0.00666                                             | 0.00771                                                 |
| (0.00786)                                                                 | (0.00690)                                            |
| Diabetes                                                                  | −0.00340                                            | −0.00782                                                 |
| (0.00927)                                                                 | (0.00976)                                            |
| Cancer                                                                    | 0.00614                                             | 0.00230                                                  |
| (0.0189)                                                                  | (0.0190)                                             |
| Lung disease                                                              | −0.0167                                             | −0.0178                                                  |
| (0.00966)                                                                 | (0.00993)                                            |
| Heart problem                                                             | 0.00666                                             | 0.00771                                                 |
| (0.00786)                                                                 | (0.00690)                                            |
| Stroke                                                                    | −0.0516                                             | −0.0448                                                  |
| (0.0233)                                                                  | (0.0243)                                             |
| Psychiatric problem                                                       | −0.0316                                             | −0.0364                                                  |
| (0.0254)                                                                  | (0.0209)                                             |
| Arthritis                                                                 | −0.00649                                             | −0.00732                                                 |
| (0.0612)                                                                  | (0.0620)                                             |
| Dyslipidemia                                                              | −0.00236                                            | −0.000276                                                |
| (0.00731)                                                                 | (0.00748)                                            |
| Liver disease                                                             | −0.00537                                            | −0.00553                                                 |
| (0.0106)                                                                  | (0.00947)                                            |
| Kidney disease                                                            | 0.0270                                              | 0.0294†                                                  |
| (0.0143)                                                                  | (0.0141)                                             |
| Stomach/ digestive disease                                                | −0.00114                                            | −0.00148                                                 |
| (0.00610)                                                                 | (0.00539)                                            |
| Asthma                                                                    | 0.0112                                              | 0.00794                                                  |
| (0.0142)                                                                  | (0.0137)                                             |
| Memory problem                                                            | 0.0346                                              | 0.0390                                                   |
| (0.0212)                                                                  | (0.0222)                                             |
| Household total wealth (in thousand Chinese ¥)                            | −0.0000000210                                        | 0.00000156                                               |
| (0.000000989)                                                             | (0.000000494)                                        |
| Annual personal income (in thousand Chinese ¥)                            | 0.000115                                             | 0.0000523                                                |
| (0.000110)                                                                | (0.0000984)                                          |
| Education high school or above                                           | 0.00444                                             | 0.00261                                                  |
| (0.00781)                                                                  | (0.00725)                                            |
| Smoke now                                                                 | 0.00218                                             | 0.00223                                                  |
| (0.00696)                                                                  | (0.00709)                                            |
| Drink alcohol daily or more often                                         | −0.000638                                           | −0.00444                                                 |
| (0.00705)                                                                  | (0.00723)                                            |
| Have UEBMI*                                                                | 0.0136                                               | 0.0167                                                   |
| (0.00912)                                                                  | (0.00858)                                            |
| Have NCMS*                                                                | 0.00366                                              | 0.00394                                                  |
| (0.00946)                                                                  | (0.00887)                                            |

Standard errors in parentheses.
Abbreviations: PHI, private health insurance; BVP, bivariate probit; IV, instrumental variable; UEBMI, urban employee basic medical insurance; NCMS, new cooperative medical scheme.

1. Results are presented as average marginal effects or incremental effects (standard error) unless otherwise specified.
2. The category of social health insurance other than UEBMI and NCMS was left out in regressions.

* p < .05.
** p < .01.
*** p < .001.
Table 5
Probit and bivariate probit regression results of physical examination on having PHI.

|                                   | Probit       | Bivariate probit |
|-----------------------------------|--------------|------------------|
| Having PHI                        | 0.190        | 0.646            |
|                                   | (0.0538)     | (0.158)          |
| Age                               | 0.00510      | 0.00485          |
|                                   | (0.000789)   | (0.000759)       |
| Male                              | 0.00673      | 0.00974          |
|                                   | (0.0172)     | (0.0164)         |
| Living in the rural area          | −0.0533      | −0.0449          |
|                                   | (0.0172)     | (0.0159)         |
| Self-reported health fair or above| −0.0116      | −0.0115          |
|                                   | (0.0172)     | (0.0164)         |
| Ever had condition                |              |                  |
| High blood pressure               | 0.0608       | 0.0579           |
|                                   | (0.0161)     | (0.0150)         |
| Diabetes                          | 0.0674       | 0.0647           |
|                                   | (0.0223)     | (0.0210)         |
| Cancer                            | 0.116        | 0.112            |
|                                   | (0.0513)     | (0.0482)         |
| Lung disease                      | 0.0222       | 0.0221           |
|                                   | (0.0218)     | (0.0208)         |
| Heart problem                     | 0.00999      | 0.00937          |
|                                   | (0.0242)     | (0.0228)         |
| Stroke                            | −0.0992      | −0.0932          |
|                                   | (0.0404)     | (0.0385)         |
| Psychiatric problem               | −0.0782      | −0.0734          |
|                                   | (0.0556)     | (0.0526)         |
| Arthritis                         | −0.00906     | −0.00866         |
|                                   | (0.0140)     | (0.0133)         |
| Dyslipidemia                      | 0.114        | 0.109            |
|                                   | (0.0195)     | (0.0182)         |
| Liver disease                     | 0.0762       | 0.0684           |
|                                   | (0.0355)     | (0.0325)         |
| Kidney disease                    | 0.000397     | 0.000496         |
|                                   | (0.0277)     | (0.0246)         |
| Stomach/ digestive disease        | 0.00599      | 0.00592          |
|                                   | (0.0155)     | (0.0150)         |
| Asthma                            | −0.00973     | −0.00848         |
|                                   | (0.0334)     | (0.0316)         |
| Memory problem                    | −0.0188      | −0.0153          |
|                                   | (0.0457)     | (0.0435)         |
| Household total wealth (in thousand Chinese ¥) | −0.00000116 | −0.00000104 |
|                                   | (0.00000257) | (0.00000244)     |
| Annual personal income (in thousand Chinese ¥) | 0.00250     | 0.00225         |
|                                   | (0.000631)   | (0.000571)       |
| Education high school or above    | 0.0504       | 0.0416           |
|                                   | (0.0239)     | (0.0228)         |
| Smoke now                         | −0.0423      | −0.0401          |
|                                   | (0.0181)     | (0.0174)         |
| Drink alcohol daily or more often | −0.0495      | −0.0463          |
|                                   | (0.0205)     | (0.0194)         |
| Have UEBMI\(^b\)                  | 0.0386       | 0.0369           |
|                                   | (0.0292)     | (0.0273)         |
| Have NCMS\(^b\)                   | −0.0509      | −0.0468          |
|                                   | (0.0271)     | (0.0256)         |
| p-Value of the correlation between error terms (p) | NA         | 0.037            |
| p-Value of over-identification test using 2SLS | NA        | 0.283            |
| N                                 | 6826         | 6823             |

Standard errors in parentheses.
Abbreviations: PHI, private health insurance; UEBMI, urban employee basic medical insurance; NCMS, new cooperative medical scheme; NA, not applicable; 2SLS, two-stage least squares.
\(^a\) Results are presented as average marginal effects or incremental effects (standard error) unless otherwise specified.
\(^b\) The category of social health insurance other than UEBMI and NCMS was left out in regressions.
p < .05.
p < .01.
p < .001.
which reflects the insurers’ profit-seeking behaviors through market competition. In light of this, lending the private sector healthcare payers with more power to allocate healthcare resources may represent an opportunity to improve social efficiency by curbing the overall costs while promoting high-value services. To that end, it is advisable to continue and even to reinforce the tax bracket policies. Individuals holding a supplementary PHI policy still only account for a tiny proportion of the population. On top of that, PHI products in China are flawed in multiple aspects that were detailed in Section 1 (Luo et al., 2016; Ng et al., 2012; Zhao & Ng, 2016). To unleash the potential of supplementary PHI, additional policies should be implemented to reinvigorate the PHI market.

The significance of leveraging PHI to encourage preventive care uptake and to reduce hospitalization may even go beyond access and state budget-sharing motivation. For instance, an important aspect of preventive care is implementing interventions to avoid infectious diseases. Of such interventions, vaccination is among the most prominent ones. Many vaccines such as influenza and pneumonia vaccines can reduce the probability of hospitalization (Song et al., 2015). During pandemic outbreaks of emerging infectious diseases, reduced healthcare utilization due to seasonal illness enables healthcare systems to spare resources for outbreak-related admission surges. The lack of such preparedness, on the other hand, possibly creates a competing need for care, overcrowded hospitals, and unattended patients, which were highlighted issues at the epicenter of the COVID-19 outbreak (Frias, 2020). Based on the findings of the present study, PHI could be an option to effectively promote high-value preventive care such as vaccines that are not part of the publicly funded immunization programs. Because private insurers are more flexible than social insurance agencies to decide which organizations and professionals to contract and what benefits to provide in China, they can more swiftly adjust their products to include such high-value care to meet the evolving market demand (Hou & Zhang, 2017).

The present analysis relied on IVs to identify the effects of supplementary PHI. Omitted variable bias due to self-selection is a major threat to the validity of the analysis of insurance effect, whereas reverse causality is another common source of endogeneity. The naïve analyses of both hospitalization and physical examination were affected by endogeneity as shown by the IV analyses. Therefore, the analyses without adjusting for endogeneity generated unreliable estimates. Specifically, the naïve analysis of hospitalization did not identify any significant effect associated with supplementary PHI whereas the IV analysis retrieved the risk-reduction effect. Had the IV analyses not been conducted, the analysis would have missed such a risk-reduction effect.

In addition to the main analyses using probit models and bivariate probit models with IVs, we also conducted several post hoc analyses using alternative specifications as robustness checks. First, we re-categorized self-reported general health into two indicators for excellent or very good and good or fair, respectively. The two indicators were then adjusted for in the multivariate regressions in lieu of the original GHI indicator. In these alternative specifications, the estimates of the marginal effects of PHI changed minimally. Specifically, the estimates in the naïve probit model and the bivariate probit model of hospitalization were $-0.0422$ (SE $0.0303$) and $-0.300$ (SE $0.0724$), both of which are close to the estimates of $-0.0428$ (SE $0.0304$) and $-0.300$ (0.0744) in the original specifications. Similarly, the alternative estimates were $0.190$ (SE $0.0538$) and $0.646$ (SE $0.158$) in the analyses of physical examination, which were the same as the estimates in the original specifications. These results suggested that the way the self-reported general health variable was grouped did not have much impact on the results of interest. Second, the concern of omitted variable bias might also be raised by the regional heterogeneity of SHI benefit and reimbursement levels, because the OOP burden of healthcare expenditure across regions could impact the uptake of PHI. To test any potential threat to the internal validity of our estimates, we created a proxy of the generosity of SHI by calculating the city/prefecture-level OOP rate of past-year inpatient costs using the subsample who had any hospitalization but only had public health insurance. Then, we examined if including this SHI generosity proxy in the covariate list of probit and BVP regressions caused any substantial change in the estimates of the effects of PHI. The estimates of the marginal effects of PHI in the analyses of hospitalization using probit and BVP remained similar as the base-case analyses $[-0.0446$ (SE: $0.0294$) and $-0.248$ (SE: $0.0799$)], so did the estimates in the analysis of physical examination [marginal effects: $0.191$ (SE: $0.0535$) and $0.651$ (SE: $0.158$)]. Hence, the regional variation of the generosity of SHI schemes did not likely cause omitted variable bias. Third, we explored Lewbel IV analyses that purely relied on the heteroscedasticity of the error term in a regression equation in which PHI was the left-hand side variable and the exogenous right-hand side variable (Lewbel, 2012). According to the results of Lewbel IV analyses, PHI decreased the probability of hospitalization by 6.04 percentage points (SE 1.90) and increased the probability of physical examination by 18.9 percentage points (SE 5.29), which are in line with the base-case IV results with regard to statistical significance and direction of effects. These analyses required less restrictive assumptions than the base-case IV analyses because they dismissed the use of excluded IVs and, for that matter, the assumptions of the excluded variables as IVs (Lewbel, 2012). However, the Lewbel IV approach is considered to produce less reliable estimates than the IV approach that uses excluded variables provided that the excluded variables hold the properties of IVs (Lewbel, 2012). Fourth, the employment status could not simply be defined as employed versus not among Chinese population because such a definition might be misleading for rural residents. Hence, an employment status variable was not included in the base case. To examine whether such an approach would have introduced potential omitted variable bias, we included in all regressions an indicator of composite employment status that represented whether the respondent was formally employed, doing agricultural work, self-employed, or working for a family business. The percentage of composite employment among those covered by PHI was 75.3%, compared with 67.8% among those not covered by PHI. The composite employment status was not statistically significantly different by PHI status ($p = .0617$). In this set of exploratory regressions, the incremental effect estimates of PHI in the hospitalization probit model, hospitalization BVP model, physical examination probit model, physical examination BVP model were $-0.0492$ (SE: $0.0303$), $-0.274$ (SE: $0.0873$), $0.192$ (SE: $0.0523$), and $0.620$ (SE: $0.176$), respectively. Since these estimates were close to the base-case results and the statistical significance inference also remained the same, the estimates of PHI in the base case were unlikely to be confounded by the composite employment indicator. Furthermore, the composite employment status indicator was not statistically significant in all regressions. Overall, these post hoc analyses confirmed the findings of the base-case analyses.
7. Limitations

Several caveats must be noted for the inference of the findings. Although we used multivariate regressions with a long list of adjusted variables and conducted IV analyses, we could not rule out the possibility of residual confounding. Addressing endogeneity is challenging in a cross-sectional study using retrospective data. On top of these, it should be noted that the IVs we chose were not guaranteed to be fully exogenous even though the weak instrument tests and the over-identification tests suggested good IV properties overall. In particular, the over-identification tests were initially used to test IV orthogonality in linear model specifications. (Cameron & Trivedi, 2009). To further examine the orthogonality of the IVs, we conducted a falsification test using a past-month outpatient visit indicator as a negative control, which was an outcome that the IV estimates were supposed to suggest no PHI effect. This is because PHI usually targets expensive services such as hospitalization instead of outpatients which are much less expensive and are relatively sufficiently addressed by basic SHI schemes. The estimated incremental effect of PHI on the probability of past-month outpatient visits was 0.417 (SE: 0.335, p = .213). Therefore, the results of the falsification test also endorsed the validity of the IVs.

In addition, the sample size of this study is relatively limited, which could result in underpowered analysis in the probit regression of hospitalization in which PHI appeared to be statistically insignificant. This issue is primarily caused by the low uptake rate of PHI among the Chinese population. An analysis of PHI in a relatively mature market would allow the inclusion of more PHI-covered individuals. However, the necessity of an analysis on the impact of PHI may accordingly diminish when PHI has been well-established and accepted.

More, some of the variables were based on self-report and might be subject to recall bias. Although electronic data provided by insurers could be relatively more reliable research resources, such data are not currently available in China to our knowledge. Notwithstanding its commonality in survey data, the impact of recall bias on the estimates of interest in the present study should not be overestimated. Report error is not very likely to have a strong, if any, association with PHI. Although more likely than the exposure variable, the outcome variables still had relatively small chances of major misreport because of their “yes or no” response type and their salient nature (Kjellsson, Clarke, & Gerdtham, 2014). In another regard, recall bias causes biased estimates of PHI effects if individuals in an exposure group systematically remembered things differently than the other group, which is not a plausible scenario in the case of the present study. Thus, recall bias should not be a major threat to the validity of the present study. As an empirical check of these assumptions, we investigated how surrogates of recall bias might associate with PHI and whether these surrogates could impact PHI effect estimates. Specifically, CHARLS required respondents to ascertain their reports of physical conditions from the last interview when a new interview was conducted, generating a list of recall error surrogates based on consistency. For example, if a respondent reported to have had hypertension during the 2013 interview but answered “no” to “whether your report of hypertension from the last interview was correct” during the 2015 interview, then the report of hypertension in 2013 was flagged with a potential error. In the first step of our empirical check, PHI was regressed on all flags of physical condition reports to examine whether these recall bias surrogates associated with PHI using a probit model. Among all flags, only the report of liver conditions significantly associated with PHI enrollment in the first step. In the second step, the flag of liver condition report error was included in the probit regressions of hospitalization and physical examination to examine if the PHI effect estimates were affected by potential errors. According to the results of the second step, the effect estimates of PHI on hospitalization (−0.042, SE: 0.0304) and physical examination (0.189, SE: 0.541) were similar to the base-case estimates. Both steps taken together, report errors of specific items could not be ruled out but did not cause major impact on PHI effect estimates.

Even more, the granularity of healthcare utilization information in the survey data was limited. For example, we were only able to use physical examination as a proxy for preventive care. Hence, we could not investigate the effects of supplementary PHI on other high-value procedures or services that represent improved access. Finally, we did not specifically establish the impact of preventive care on hospitalization. This is a complicated yet important analysis in its own right and poses equally challenging endogeneity issues as supplementary PHI. We relied on established evidence in the literature for the connection between preventive care and hospitalization (Kolstad & Kowalski, 2012; Wallace & Sommers, 2016) with the recognition of a potential lack of generalizability of such evidence.

8. Conclusions

Supplementary PHI in China may be effective to improve access to high-value preventive care and to reduce the expensive medical occurrence. Overall, it increases efficiency in the healthcare sector and has the potential to address additional preventive care need. Although future studies on ascertaining the effects of supplementary PHI on accessing expensive services and reducing out-of-pocket financial burden are required to completely understand the utility of supplementary PHI, the present study provided preliminary evidence that the China healthcare system can benefit from engaging PHI as supplements to SHI.

Declaration of Competing Interest

The authors claim no conflicts of interest related to the submitted work. The authors did not receive any grant from funding agencies in the public, commercial, or not-for-profit sectors for the submitted work.
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