Investigation of Service Distortion in China's New Cooperative Medical Scheme

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Abstract

The Chinese government implemented a nationwide health insurance program called the New Cooperative Medical Scheme (NCMS). The literature has found that this program failed to provide sufficient financial protection. One possible reason is that some insurers undercover the health services that involve significant medical expenses. This study aims to understand the degree of distortion in the NCMS benefit plan and inform program modification to improve the effectiveness. We evaluate the service-level coverage of NCMS through quantifying each service's shadow price. Based on China Health and Nutrition Survey data, we divide the whole sample into four geographical regions and assess each region's population health status, distribution of health spending, and shadow prices of different health services. To inform NCMS benefit modification, we investigate the distortion under different risk-adjusted premiums empirically. Our results reveal challenges of financial sustainability faced by the NCMS program, especially in the Northeast region. The NCMS plan tends to undercover the services that are predictable and negatively correlated with plan profits, such as inpatient treatments. We also find that the efficiency of the NCMS can be improved if its risk premiums are adjusted based on individual demographic characteristics and disease history.

Keywords: health insurance; rural China; adverse selection; service-level benefits

1. Introduction

China faces a significant challenge to provide affordable and easy-access healthcare services to all the residents, especially those living in less-developed rural areas. The challenge started in 1978 when the government transferred agricultural communes to household production units, and over 90% rural population lost their health insurance (Yip and Hsiao, 2009; You and Kobayashi, 2009). Additionally, the central government reduced its subsidy on total medical expenditure from 32% in 1978 to 15% in 1999 (CHEI, 2009), and many public health facilities became profit-driven and relied on sales of drugs and services as a primary source of income (Barber and Yao, 2011; Wagstaff et al., 2009). Without any health insurance, many rural households could not afford increasing healthcare costs and resulted in medical impoverishments. In response to this threat, the central government finally piloted a public rural health insurance scheme in 2003, which was called the *New Cooperative Medical Scheme* (NCMS), and expanded it rapidly nationwide. Since then, this public insurance program's participation rates increased from 13% to 98.8% in 2015 and covered 670 million rural residents (NHFPC, 2015). After 2016, some regions combined NCMS with Urban Resident Medical Insurance. In 2018, NCMS was replaced by Urban and Rural Resident Medical Insurance (URRMI) in most areas.

One potential reason of NCMS's discontinuity was that this program seemed to fail to provide sufficient financial protection (Hou et al., 2014; Yip and Hsiao, 2009; You and Kobayashi, 2009; Yu et al., 2010). Empirical evidence suggested that NCMS participants had higher out-of-pocket health spending (Wagstaff et al., 2009; Zhou et al., 2009) and increased likelihoods of being impoverished by medical expense compared with non-participants (Wagstaff and Lindelow, 2008). Why was NCMS less successful in achieving its primary goal of preventing the rural population from the medical impoverishment? This study answers this question by investigating the inefficiency of NCMS service-level benefit designs. We start by introducing the program infrastructure and the role of governments and then discuss the potential adverse selection problem and how it induces governments' selective incentives.

1.1 China's New Cooperative Medical Scheme

The NCMS was a government-led public health program funded by all levels of governments, including the central government, provincial governments, and county governments. In 2017, the annual per-person NCMS premium was RMB 630 (USD 99.24), which consisted of RMB 180 from the individual and RMB 450 from governments. The weights of subsidies from the central and provincial governments were higher for poorer counties (Meng and Xu, 2014).

Figure 1 illustrates the program infrastructure. At the central level, the Ministry of Health offered general guidelines and evaluated the NCMS information system with provincial authorities (Brown et al., 2009). To encourage participation, the central government conditioned NCMS subsidy contribution to the counties that achieved a minimum of 80% participation level (Hou et al., 2014; You and Kobayashi, 2009). At the provincial level, health departments provided more detailed guidelines and technical assistance to county governments. The provincial authority also monitored claims data in the NCMS information system collected by counties. Finally, the county governments were in charge of the NCMS program, including its risk pooling, administrative arrangements, and benefit designs. Each county had an NCMS office to implement this program and managed the funds in a state-owned bank account specifically for this program.

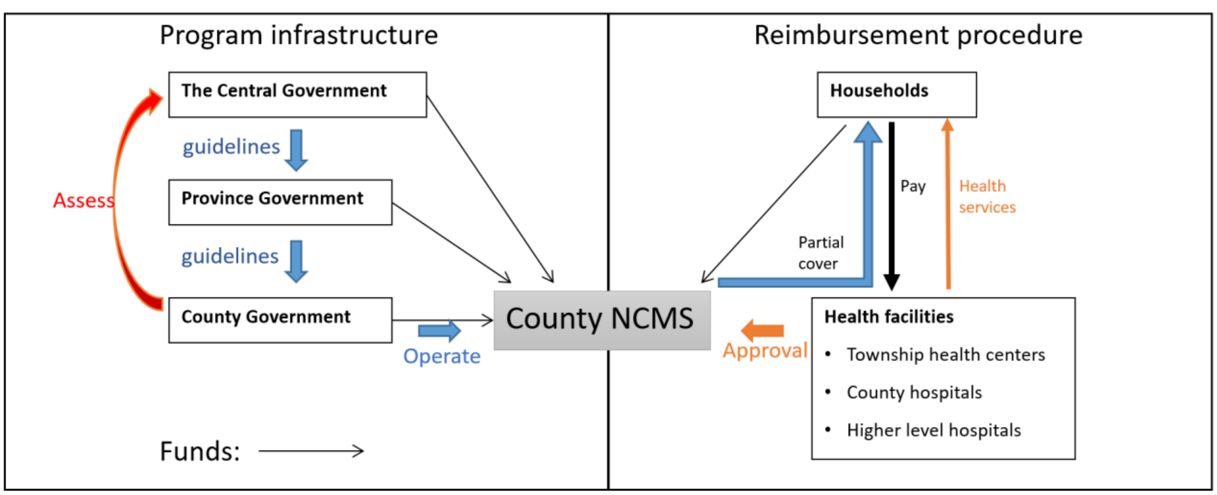

Figure 1 China's NCMS infrastructure and functions.

The extensive decentralization of the NCMS implementation encouraged county governments to experiment with different benefit designs, which were subject to guidelines from the central and provincial authorities. For example, the local governments could not refuse participants as long as they had rural residence status (*hukou*), and the enrollment had to be at the household level. Researchers found considerable variations in the NCMS reimbursement rules and benefit distributions by region (Barber and Yao, 2011; Brown et al., 2009). The insurance benefit package covered inpatient and outpatient care as well as preventive health services (e.g., physical examination and screening). To qualify for reimbursements, participants in some counties had to pay their entire medical bills to the health facility approved by the county NCMS office and then submit receipts. In other counties, enrollees could obtain medical bills from the approved health facility reduced by the amount covered by NCMS. The county administrators had incentives to support the local economy because the reimbursement rates were higher for township health centers and county hospitals than for higher level hospitals. The NCMS service coverages were very limited due to a small budget, which caused problems such as large deductibles, low ceilings, and high coinsurance rates (Li and Zhang, 2013; Meng and Xu, 2014; Wagstaff et al., 2009).

1.2 Adverse selection in the health insurance market

Adverse selection was a concern of the NCMS because county governments could not reject high-cost enrollees or charge this group an inflated price. According to Rothschild and Stiglitz (1978), adverse selection occurs when insurers are uncertain about the health risk levels of their enrollees. The asymmetric information enables high-risk individuals to purchase the more generous insurance contracts designed for low-risk individuals and increase the total cost of the plan. Additionally, healthier people expecting to use fewer services may leave the market and further increase the financial risk faced by insurers.

Empirical studies have demonstrated the NCMS suffers from the adverse selection problem, despite its achievement of high participation rates and required household-level participation (Wagstaff et al., 2009; You and Kobayashi, 2009). For example, Wagstaff et al. (2009) found households with a higher portion of chronically sick members were more likely to participate in the NCMS. A similar rural medical scheme established by a Harvard research team in rural China also revealed that enrolled individuals had worse health status than non-enrolled individuals (Wang et al., 2005). Moreover, public mistrust of the local governments made relatively healthy rural people reluctant to participate in NCMS, thinking most of their contributions were used to help unhealthy people.

1.3 Incentives for service-level selection

Adverse selection can induce inefficient service rationing (Layton et al., 2017), that is; the service-level plan benefits are distorted by the insurers to discourage high-cost people and attract good risk. This strategy is also called "indirect selection" (Breyer et al., 2011). Evidence of service-level distortion has been widely found in Medicare (Brown et al., 2014; Cao and McGuire, 2003; Carey, 2017; Newhouse et al., 2015), marketplaces (Geruso et al., 2016; McGuire et al., 2014), and employer-based insurance (Eggleston and Bir, 2009).

Glazer and McGuire (2000) originated this line of literature. They derived an optimal risk adjustment and showed that insurers tended to under-provide the services more attractive to people who are sicker and over-provide services commonly demanded by healthier participants. Building on this idea, Frank et al. (2000) derived profit-maximizing shadow prices to empirically quantify under- and over-provision of a health service. They found that a health service with a higher shadow price tends to be underprovided because more costs are generated relative to plan revenues.

Ellis and McGuire (2007) extended the research of Frank et al. (2000) and developed an index to measure the incentive to increase shadow prices based on a sample of Medicare beneficiaries. The main results suggested that insurers underprovided highly predictable health services (i.e., hospice care, inpatient visit) or health services highly correlated with total spending (i.e., home health care). By applying this method to four managed and non-managed care plans, Ellis et al. (2013) found the service-level distortions were similar across all plans, and the traditional comprehensive plan was least selective in service coverages. On average, the actual services covered by managed care plans were more consistent with the theoretical prediction of selection indices. Similar analyses were conducted in private health insurance markets (McGuire et al., 2014).

Because of the extensive decentralization of the NCMS infrastructure, incentives of county governments played a crucial role. Given the fixed program premium per person, these governments had to manage a trade-off between increasing NCMS benefits to qualify the matching subsidy and minimizing the variable program costs. The concern regarding controlling costs was salient, especially in the poor and sick counties. Those county governments could make the reimbursement procedure cumbersome, restrict benefits to emigrants, or manipulate the policy of service coverage. Additionally, like private insurers, county governments might undercover the health services that involve significant medical expense and ignore their residents' disease profiles and financial needs (Brown et al., 2009; Yip and Hsiao, 2009). According to Yip and Hsiao (2009), the NCMS was ineffective at reducing medical impoverishment because its benefits packages often ignored high-cost health problems.

Additionally, county governments might provide "too much" benefit for health services for relatively healthy people to attract good risk. Either selective incentive may distort the efficiency level of the NCMS benefit plans and contradict the primary goal of this program.

The literature has found insurers' selective incentives in many health insurance programs, but most of these studies have focused on programs in developed countries. In this study, we use China Health and Nutrition Study (CHNS) data to examine which health services are under- or over-covered for rural residents in a developing country. We develop a regional shadow price to measure service-level distortion and show how the shadow price is affected by various population health status and health expenditure distributions in different regions of China.

When building theoretical models, researchers have often assumed the insurers expected the same insurance benefits as the program participants, which may not be appropriate. To fill this gap, our study assumes that local governments are less informed than participating households regarding expected benefits. This modification enables us to assess the changes in service-level distortion under the asymmetry of information between governments and households. Finally, we determine to what extent the inefficiency can be reduced by adjustments to the risk premium and provide suggestions for future health policy designs.

2. Theoretical Model

This section characterizes the governments' incentives to ration the NCMS benefits by using a principal–agent model originally developed by Frank et al. (2000). Our modified model has three stages: local governments firstly design the benefit plan of the NCMS based on their knowledge of the distribution of household health spending and participation decisions. Next, a household decides whether to participate in the NCMS by comparing the resulting utility with its reservation utility. Finally, households incur medical expenditures, and the NCMS covers a portion of household spending.

2.1 Agents: participation decisions

Before deciding whether to participate the NCMS, households are uncertain about their future health status and insurance benefits. To simplify the model, we treat a household i as a single agent. Suppose there are only two possible outcomes: being healthy or unhealthy in the next year with a probability λ_i for the unhealthy type, only known by the household. Household i's expected benefit of service s is a weighted average of two benefit outcomes

$$\widehat{m}_{is} = \lambda_i \cdot \overline{m}_{is} + (1 - \lambda_i)\underline{m}_{is},\ \ 0 < \lambda_i < 1 \text{ for } i = 1, 2, \dots, N \tag{1}$$

where $\overline{m}_{is}$ refers to the NCMS benefit of service s received if the household is the unhealthy type, and $\underline{m}_{is}$ is the benefit if the household is the healthy type. Let $\widehat{m}_i = [\widehat{m}_{i1,}\, \widehat{m}_{i2}, \dots, \widehat{m}_{iS}]$ be a set of expected plan benefits over $s = 1, 2, 3, \dots, S$ services. The utility of participating in the NCMS for household i is

$$u_i(\widehat{m}_i) = v_i(\widehat{m}_i) + \ \mu_i - c_i, \text{ where } v_i(\widehat{m}_i) = \textstyle\sum_s v_{is}(\widehat{m}_{is}). \tag{2}$$

The first component $v_i(\widehat{m}_i)$ is the total valuation of the expected NCMS benefit. If the valuation is assumed to be additive, $v_i(\widehat{m}_i)$ is a sum of $v_{is}(\widehat{m}_{is})$ defined as household i's valuation of the expected insurance benefit of service s. We assume that $v'_{is}(.) > 0$, $v''_{is}(.) < 0$, and $v_{is}(.)$ is independent of other health services $s' \neq s$. The second component μ_i indicates utility unrelated to the benefits from the NCMS and household health types, and c_i is household i's cost of enrolling and obtaining insurance benefits. For simplicity, we assume that c_i is not type-dependent. The validity of this assumption may depend on reimbursement procedures. The cost is likely to be type-independent if insured households receive discounted medical bills directly from health facilities, because the cost of obtaining an insurance benefit is not related to total medical spending. However, if the reimbursement requires the enrollees to submit receipts case-by-case, unhealthy households may encounter a higher cost because they must make more insurance claims.

Suppose the household does not participate in the NCMS, it stays merely uninsured[1], and $\hat{u}_i^0 = \lambda_i \cdot \bar{u}_i^0 + (1 - \lambda_i)\underline{u}_i^0$ is the expected reservation utility[2]. If $u_i(\widehat{m}_i) > \hat{u}_i^0$, the household will participate in the NCMS; thus, the probability of participation is

$$Prob(u_i(\widehat{m}_i) > \hat{u}_i^0) = Prob\left(\mu_i > \hat{u}_i^0 + c_i - v_i(\widehat{m}_i)\right) \tag{3}$$

Assuming μ_i follows a certain distribution, we can express the probability through its cumulated distribution function, denoted as $F_i(.)$

$$Prob(u_i(\widehat{m}_i) > \hat{u}_i^0) = 1 - \mathrm{F}[\hat{u}_i^0 + c_i - v_i(\widehat{m}_i)] \equiv n_i(\widehat{m}_i, \hat{u}_i^0, c_i) \tag{4}$$

This equation indicates that a household is more likely to participate in the NCMS if it expects a higher plan benefit ($\frac{\partial n_i}{\partial \widehat{m}_i} > 0$), a lower reservation utility ($\frac{\partial n_i}{\partial \hat{u}_i^0} < 0$), and a lower cost ($\frac{\partial n_i}{\partial c_i} < 0$).

2.2 Shadow price

Following Keeler et al. (1998), we use shadow prices to measure the generosity of the plan coverage over different services. In the NCMS program, the shadow price p_s is defined as a government-assessed threshold that a household's marginal valuation must exceed to qualify for NCMS reimbursements:

$$v_{is}'(\widehat{m}_{is}) = p_s \tag{5}$$

[1] In China, most rural residents cannot afford other private health insurance plans, so the reservation utility is defined as the utility obtained when the household does not purchase any health insurance

[2] Because a healthy household has a lower probability of paying substantial medical expenses, the reservation utility of the healthy type is higher than unhealthy type ($\bar{u}_i^0 < \underline{u}_i^0$).

A household expects its NCMS benefit of service s by solving the inverse demand function $\hat{m}_{is}(p_s) = v_{is}'^{-1}(p_s)$. Figure 2 illustrates demand curves of two households: a healthy household i and an unhealthy household j. Given the same shadow price p_s^0, this example shows that the unhealthy household receives more insurance benefits because it has higher demand of service s than the healthy type. If the plan is less generous regarding service s, one strategy is to increase the shadow price to p_s^1 (i.e., decreasing the NCMS reimbursement rate or increasing the deductible of this service); then, both households receive less benefit. This framework enables us to evaluate relative service coverage of an insurance plan. Specifically, the higher the p_s, the less coverage of service s provided by the NCMS.

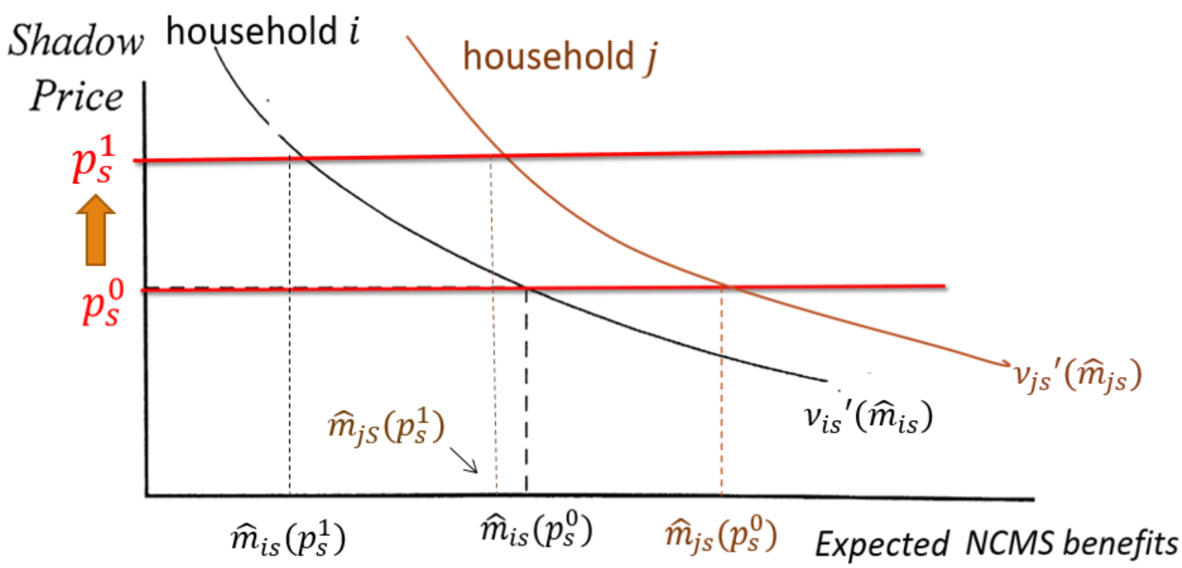

Figure 2 Shadow price of service s, and demand of benefits for two households.

Because the shadow price reflects the marginal valuation of a service, the local government should set shadow prices equally among different services to achieve socially optimal outcomes.

$$p_s^* = v_{is}'(\widehat{m}_{is}) = v_{is'}'(\widehat{m}_{is'}) = p_{s'}^* \text{ for } s \neq s' \;\; \forall s = 1, 2, 3, \ldots, S \tag{6}$$

Otherwise, if $p_s^* > p_{s'}^*$, households' utilities can be improved by increasing more desired coverage for service s and reducing the benefit for less desired service s' until $v_{is}'(\widehat{m}_{is}) = v_{is'}'(\widehat{m}_{is'})$.

2.3 Principal: financial incentives

2.3.1 Optimal shadow price without asymmetric information

We assume that a county government sets an optimal vector of shadow prices $\boldsymbol{p} = [p_1, p_2, \ldots, p_S]$ to maximize profit. Although the objective of profit-maximization often applies to private companies instead of governments, we assert this is a substantial concern for GDP-driven local governments in China. Additionally, the assumption of maximizing profit is supported by evidence in the literature that counties often maintain a large surplus of NCMS funds every year to avoid bankruptcy (Ke et al., 2009). If the government shares the same expectations as the households, the problem in the first-best case becomes

$$\max_{\boldsymbol{p}} \pi(\boldsymbol{p}) = \underbrace{\sum_i [n_i\,[\widehat{m}_i(\boldsymbol{p}), \hat{u}_i^0, c_i]}_{Probability\ of\ participation} \times \underbrace{[r_i - \sum_s \widehat{m}_{is}(p_s)]\,]}_{Expected\ plan\ profit\ from\ household\ i} \tag{7}$$

where r_i denotes the risk premium collected from household i and is considered earnings by the government. The government treats the total benefit $\sum_s \widehat{m}_{is}(p_s)$ as costs; thus, the expected profit from household i is $\pi_i = r_i - \sum_s \widehat{m}_{is}(p_s)$.

After solving this equation, we obtain the profit-maximizing shadow price:

$$p_s^* = \frac{\sum_i n_i \widehat{m}_{is}}{\sum_i \mathrm{F}_i' \widehat{m}_{is} \cdot (r_i - \sum_s \widehat{m}_{is})} = \frac{\sum_i n_i \widehat{m}_{is}}{\sum_i \mathrm{F}_i' \widehat{m}_{is} \cdot \pi_i} \tag{8}$$

From the perspective of the principal, the numerator represents the total expected cost of covering service s. If the cost is high, a local government has the incentive to increase p_s and provide less coverage for this health service. The denominator characterizes the marginal benefit of increasing participation. A high and positive margin benefit lower the shadow price, that is, the local government will cover service s more as this strategy attracts "good-risk" enrollees ($\pi_i > 0$).

2.3.2 Selection index: how service characteristics affect the shadow price

Next, we use a selection index to measure the government's incentive to ration service s by increasing its shadow price. By following Ellis et al. (2013), we define the selection index as

$$\mathrm{I_s} = \frac{d\pi}{dp_s} \times \frac{1}{N\overline{m}_s\sigma_\pi}, \text{ where } \overline{m}_s = \frac{1}{N}\sum_i n_i\widehat{m}_{is}, \tag{9}$$

and σ_π is the standard deviation of π_i.

The selection index is a unitless measure that can be positive, negative, or zero. When $\mathrm{I_s} > 0$, the higher the selection index, the higher the incentive of the local government to increase the shadow price (undercover service s). A negative selection index indicates $\frac{d\pi}{dp_s} < 0$, that is, the government has an incentive to over cover service s by decreasing its shadow price. If no service-level distortion is observed, the selection index should be close to zero.

When evaluated at $\mathrm{p_s} = 1$, the selection index becomes (see Appendix A for details)

$$\mathrm{I_s} = \frac{d\pi}{dp_s} \times \frac{1}{N\overline{m}_s\sigma_\pi} = \underset{(-)}{e_s} \cdot [\underset{(?)}{\rho_{\mathrm{m_{is}},\pi_i}} \cdot \underset{(+)}{cov(\widehat{m}_{is})} + \underset{(?)}{C}] \tag{10}$$

where $cov(\widehat{m}_{is}) = \hat{\sigma}_s/\overline{m}_s$, $C = \frac{\overline{\pi}-1}{\sigma_\pi}$, and $\overline{\pi} = \frac{1}{N}\sum_i n_i\pi_i$

Components of $\mathrm{I_s}$ provide more insights on how service characteristics affect selective incentives. The selection index of service s is affected by the normalized average plan profit (C), demand elasticity of this service (e_s), the coefficient of variation of households' expected benefits ($cov(\widehat{m}_{is})$), and the correlation coefficient between $\widehat{m}_{is}$ and π_i. Given that C is a constant, we discuss how e_s, $cov(\widehat{m}_{is})$ and $\rho_{\mathrm{m_{is}},\pi_i}$ affect governments' selective incentives.

Implication 1: e_s is the demand elasticity of service s and assumed to be negative. I_s increases as the demand for health service s become more elastic. The intuitive explanation is this: since households' demand of this health service is very sensitive to the shadow price, the government can considerably reduce the program cost on service s by increasing its shadow price.

Implication 2: The coefficient of variation $cov(\widehat{m}_{is})$ captures the predictability of the NCMS benefit of service s. I_s increases as households can predict $\widehat{m}_{is}$ better (with larger variation), such as reimbursement for treatments of chronic diseases. $cov(\widehat{m}_{is})$ may be small if the service is less-predictable, such as reimbursement for treatments of injury.

Implication 3: $\rho_{\mathrm{m_{is}},\pi_i}$ is the correlation coefficient between $\widehat{m}_{is}$ (expected NCMS benefit of service s) and the plan's profit π_i from each household. When the risk premium is fixed, $\rho_{\mathrm{m_{is}},\pi_i}$ is usually less than zero because π_i=$r_i - \sum_s \widehat{m}_{is}$. However, if risk premium is positively correlated with $\widehat{m}_{is}$, $\rho_{\mathrm{m_{is}},\pi_i}$ can be zero or even positive. This implication indicates that appropriate adjustments of the risk premium could reduce the incentive to under-provide this service. For example, if higher risk premiums can be collected from unhealthy-type households, local governments will distort the NCMS benefit less.

2.3.2 Government Uncertainty: how population characteristics affect the shadow price

A notable complication of this problem is that $\widehat{m}_{is}(p_s) = \lambda_i \cdot \overline{m}_{is} + (1-\lambda_i)\underline{m}_{is}$ is household i's private information, which is unknown to the county government. In the second-best case, the principal must approximate λ_i, $\overline{m}_{is}$, and $\underline{m}_{is}$ based on its available information from the population. For λ_i, we assume that the local government does not know the probability of being the unhealthy type for each household, but knows a λ portion of the population is unhealthy and approximates $\lambda_i \approx \lambda$. For $\overline{m}_{is}$ and $\underline{m}_{is}$, the plan can predict a baseline insurance benefit m_{is}^B based on household i's observable characteristics and adjust m_{is}^B downward or upward by its belief in the different NCMS benefit distributions between healthy and unhealthy groups. As shown in figure 2, unhealthy households usually demand a higher insurance benefit than healthy households. We introduce parameter θ_s to capture the discrepancy in the average NCMS benefit of service s between two groups and assume the government approximates $\overline{m}_{is} \approx \bar{\theta}_s m_{is}^B$ and $\underline{m}_{is} \approx \underline{\theta}_s m_{is}^B$. Then, household i's insurance benefit approximated by the local government is

$$\widehat{m_{is}(p_s)} \equiv \lambda\overline{\theta}_s m_{is}^B(p_s) + (1-\lambda)\underline{\theta}_s m_{is}^B(p_s) = \left[\lambda\overline{\theta_s} + (1-\lambda)\underline{\theta_s}\right] m_{is}^B(p_s) = \Theta_s m_{is}^B(p_s),\ \Theta_s = \left[\lambda\overline{\theta_s} + (1-\lambda)\underline{\theta_s}\right] \tag{11}$$

With the uncertainty of expected household benefits, the government needs to solve the following profit-maximizing problem:

$$\max_{\boldsymbol{p}} \pi(\boldsymbol{p}) = \sum_i n_i \left[\widehat{m_i(\boldsymbol{p})}, \hat{u}_i^0, c_i\right] \cdot [r_i - \sum_s \widehat{m_{is}(p_s)}]$$

Solving for the second-best shadow price, we obtain (see Appendix B for calculations)

$$p_s^{second} = \frac{\sum_i n_i m_{is}^B}{\sum_i \mathrm{F}_i' m_{is}^B \cdot (r_i - \sum_s \Theta_s m_{is}^B)} \tag{12}$$

Equation (12) provides additional insights into how population health status affects the optimal shadow prices when asymmetry of information between governments and households is considered.

Implication 4: The NCMS plan covers less if the county has a higher portion of unhealthy residents. We easily prove that $\frac{\partial p_s^{second}}{\partial \lambda} = \frac{\partial p_s^{second}}{\partial \Theta_s} \cdot \frac{\partial \Theta_s}{\partial \lambda} > 0$. Due to the concern of cost control, a local government has the incentive to increase the price of (or undercover) health services if a higher portion of its counties' residents is unhealthy. This incentive may explain why the NCMS failed to provide sufficient financial protection in those areas with health disparities.

Implication 5: The greater the discrepancy in the NCMS benefits distribution between two types of households, the more upward the distortion of p_s^{second}. Let $\Delta\theta_s = \bar{\theta}_s - \underline{\theta_s}$, and $\frac{\partial p_s^{second}}{\partial \Delta\theta_s} = \frac{\partial p_s^{second}}{\partial \Theta_s} \cdot \frac{\partial \Theta_s}{\partial \Delta\theta_s} > 0$. A health service tends to be under-covered when unhealthy households demand much more insurance benefit than healthy households because in this case, not being able to identify household types costs the program a substantial amount of money. A good example is the hospitalization of chronic diseases. Because unhealthy people require more hospitalization services than healthy people, local governments have the incentive to distort the shadow prices of hospitalization service upward to save costs. If there is no difference in the demands of service between unhealthy and healthy participants, the government does not have to worry about not knowing household health status.

Next, we demonstrate how to identify potential distortions in the NCMS benefit designs using empirical data.

3. Data and Variables

3.1 Data

We used CHNS data from 2009 and 2011. The CHNS was a collaborative project between the Carolina Population Center at the University of North Carolina at Chapel Hill and the Chinese National Institute for Nutrition and Health. This survey used a multistage, random duster process to draw a sample of Chinese households from 9 provinces and 3 municipalities directly under the central government and collected their nutrition, health behaviors, outcomes, and socioeconomic status. These 12 provinces and municipalities were divided into four regions (Xu et al., 2015): 1) Northeast China: Heilongjiang and Liaoning; 2) East Coast: Shandong, Shanghai and Jiangsu; 3) Central China: Beijing, Henan, Hubei, and Hunan and 4) Western China: Chongqing, Guangxi and Guizhou. The CHNS data was longitudinal for the following survey years: 1989, 1991, 1993, 1997, 2000, 2004, 2006, 2009, and 2011.

For our purpose of calculating regional shadow prices, there were four data problems in the CHNS data that had to be addressed. First, the CHNS's reported insurance benefits were not restricted to the NCMS program. Second, there was no direct question about health status in the 2009 and 2011 surveys. Third, the survey did not provide detailed service-level spending or diagnosis codes that could be used to divide spending. Fourth, although the NCMS enrollment was for 1 year, the survey collected health spending information only from the past 4 weeks and therefore had many missing values. The empirical strategies to address these problems are as follows.

Problem #1: Non-separate insurance benefits

Respondents reported their health spending and percentages covered by their health insurance, but the coverage percentages were not separated by the types of insurance. To restrict insurance benefit to only the NCMS program, we excluded non-NCMS participants and those NCMS participants who purchased additional health insurance from the sample; thus, the insurance benefits were restricted to the NCMS program.

Problem #2: No health status question

Given that the CHNS did not ask a question about health status in 2009 and 2011, the second problem was how to classify the participants into the *healthy* and *unhealthy* categories. We developed two indicators for unhealthy based on available health information. The first indictor was self-reported and based on the following question on the CHNS: Has a doctor ever told you that you suffer from high blood pressure/diabetes/myocardial infarction/stroke/ cancer/asthma? Thus, a healthy person can be identified if the answer was "no" to all these questions; otherwise, we placed the person in the unhealthy category. One limitation of self-reported health status is that this measure may not reflects the population's health status but their knowledge of diagnosed diseases. The second indicator was based on physical examination results, including blood pressure, height, weight, and health conditions, as assessed by a physician. The unhealthy category comprised participants identified with high blood pressure, obesity (BMI>29[3]), or at least one disability[4].

Problem #3: Type of services

The third problem was how to divide spending into separate health services. The CHNS survey asked a series of questions about individual spending on different medical-related activities. According to the classification of health services provided by Berndt et al. (2000) and Qian et al. (2009), we partitioned spending into four mutually exclusive services: self-treatment/informal care, outpatient treatments, inpatient treatments, and preventive health services (i.e., health examination, screening tests). Because the NCMS covered only formal health care, we excluded the category of self-treatment/informal care when predicting insurance benefits.

Problem #4: Only monthly spending

Individuals' health expenditures were recalled for the 4 weeks prior to the CHNS survey interview; therefore, many respondents reported no health spending. For the spending on

[3] The Chinese BMI cut-off point for obesity is obtained from Who, E.C., 2004. Appropriate body-mass index for Asian populations and its implications for policy and intervention strategies. Lancet (London, England) 363, 157..
[4] Disability status satisfies at least one of these conditions: angular stomatitis, goiter, blind one or both eyes, lose one or both arms, lose one or both legs.

inpatient and outpatient services, we treated those missing values as zero if the respondents replied "no" to the question "During the past 4 weeks, have you been sick or injured?" Otherwise, we maintained those values as missing. To predict annual spending on different services, we predicted an individual's monthly health spending and sumed these up as that individual's total spending in 1 year.

3.2 Summary Statistics

Table 1 provides detailed summary statistics and one-way ANOVA results of differences in means between regions. We find that monthly health expenditures are similar between regions. Compared with the other two types of services, inpatient and outpatient treatments cost the most and have large standard deviations. On average, the monthly total health spending ranges from RMB 100 to 200. Significant p-values suggest substantial differences in NCMS service-level reimbursement rates between regions, but the total insurance benefits are similar. For example, NCMS programs in Central China tend to be the most generous (RMB 79.55), especially for inpatient services and preventive health services. The NCMS program's reimbursement rates on inpatient and preventive services are much lower in the East Coast region, and its average monthly reimbursement was only RMB 24.02 in 2011.

For demographic characteristics, age, education level and household annual income are significantly different between regions. With an average of 30.94 years old, Northeast China respondents are younger than those in other regions and had more years of education. We also find that residents of the East Coast have much higher annual household incomes (i.e., on average RMB 46,066), whereas the Western region has the lowest average household income (i.e., RMB 32,142).

[Table 1 to be here]

4. Empirical Method

To calculate the selection indices and shadow prices in equations (10) and (12), we need to estimate four theoretical parameters: the risk premium (r_i), baseline insurance benefit on service s (m_{is}^B), the portion of unhealthy population λ in a region, and the parameters θ_s, which captures discrepancy in benefit distributions between the healthy and unhealthy types. The parameter λ can be approximated as the percent of unhealthy people in a region. For each region, $\underline{\theta}_s$ and $\overline{\theta}_s$ are calculated as the ratio of group median insurance benefit of service s over the population median benefit of this service as follows:

$$\bar{\theta}_s = \frac{median\ m_{is}^B\ of\ unhealthy\ people\ in\ region\ A}{median\ m_{is}^B\ in\ region\ A} \tag{13}$$

$$\underline{\theta_s} = \frac{median\ m_{is}^B\ of\ healthy\ people\ in\ region\ A}{median\ m_{is}^B\ in\ region\ A}$$

Next, we discuss how to construct m_{is}^B and risk premium r_i in subsections 4.1 and 4.2.

4.1 Baseline NCMS Benefit

We assume the government can predict a household's baseline NCMS benefit of service s based on this household's characteristics. The ideal dependent variables should be health spending on different services covered by the NCMS. Due to too many missing values in "percent of spending covered by insurance," we must approximate m_{is}^B by multiplying predicted individual health spending on service s by the community average "percent of spending covered by insurance" for service s. Additionally, we do not know what information the government uses to predict household benefits. Thus, we assume two information sets as an illustration: a less-information set and a more-information set. The actual functional forms and variables in each set are discussed in the section of model specifications.

The next question is what empirical method to choose. The literature has used a variety of empirical models to predict medical expenditures, such as ordinary least squares (OLS) models (Chang et al., 2010; Chang and Weiner, 2010), weighted least squares models (Pope et al., 2004; Zhao et al., 2005), two-part models (Ellis et al., 2013; McGuire et al., 2014; Yu, 2017), generalized linear models (GLM) (Ellis and McGuire, 2007), and quantile regressions (Babiarz et al., 2012; Kowalski, 2016).

For each information set, we tried OLS, GLM, two-part models, and quantile regression to predict individual total health spending in 2011. Preliminary results suggested that the two-part model with GLM in the second part had the highest predictive power. Therefore, we focus on two-part models in the following analyses. For the GLM part, we follow the recommendations by Manning and Norton (2013) and find the combination of a log link function and a gamma distribution of the errors produces the lowest Bayesian information criterion.

The two-part model consists of a probit model and a conditional exponential model. Under the more-information set, it is specified as

$$\Pr\left(y_{s,2011} > 0 \,\middle|\, \boldsymbol{DE}, \mathrm{y}_{\mathrm{s},2009},, \boldsymbol{R}, \boldsymbol{M}; \boldsymbol{\alpha_1}\right) = \Phi(\boldsymbol{DE}, \mathrm{y}_{\mathrm{s},2009}, \boldsymbol{R}, \boldsymbol{M}; \boldsymbol{\alpha_1}) \tag{14}$$

$$\mathrm{E}\left(y_{s,2011} \,\middle|\, y_{s,2011} > 0, \boldsymbol{DE}, \mathrm{y}_{\mathrm{s},2009}, \boldsymbol{R}, \boldsymbol{M}; \boldsymbol{\alpha_2}\right)] = \exp(\boldsymbol{DE}, \mathrm{y}_{\mathrm{s},2009},, \boldsymbol{R}, \boldsymbol{M}; \boldsymbol{\alpha_2})$$

The dependent variable $y_{s,2011}$ is an individual's health spending on service s in 2011. $\boldsymbol{DE}$ is a vector of individual-level demographic variables, including age, age squared, a sex indicator, completed years of education, household net income, and interactions between the sex and age variables. We also include $\mathrm{y}_{\mathrm{s},2009}$: individual i's prior spending on service s. Finally, regional indicators ($\boldsymbol{R}$) and monthly indicators ($\boldsymbol{M}$) are used to control regional and time effects. Next, we predict health spending in a region by setting the regional dummies to that region. The error terms are assumed to be correlated within communities. The less-information set is constructed by excluding $y_{s,2009}$, years of education, household income, and $\boldsymbol{M}$ from the full set of explanatory variables. This model was estimated using STATA 14.0 (StataCorp, 2015).

4.2. Risk premium

We calculate shadow prices based on three types of risk premium: 1) actual flat-rate risk premium per individual in 2011; 2) average NCMS benefit per individual in 2009; and 3) risk-adjusted premium based on the Ambulatory Care Group (ACG) algorithm. Because the participation was at the household level, we aggregate the individual risk premium to their household total. For the first type, we evaluate the shadow prices based on the actual risk premium of RMB 230 in 2011. The risk premium is fixed regardless of participants' types, and therefore is likely to cause adverse selection. The second type of risk premium is sample average NCMS benefit in 2009. This risk premium is still constant in a region, but adjusted by the actual regional cost of the NCMS program. Finally, we develop the third risk-adjusted premium to observe how it would affect the distortion.

The third risk-adjustment algorithm follows the ACG algorithm developed by Weiner et al. (1996). The ACG risk-adjustment approach classified *International Classification of Diseases, 9th Revision, Clinical Modification* (ICD-9-CM) diagnosis codes into distinct Ambulatory Diagnosis Groups (ADG) and assigned individuals to one or more ADGs based on their previous diagnoses. Next, the risk premium was calculated by adding up the expected costs of each ADG assigned to an individual. The original study regressed individual annual medical expenditure on four dummy variables: being male, years over 65, ever disabled and Medicaid eligibility, and indicators of 13 ADG groups. The ACG-adjusted risk premium was the predicted healthcare spending based on individual characteristics and diagnoses documented in the last year.

This study could not apply the ACG algorithm directly because of data limitations. This phenomenon occurred for a few reasons. First, diagnosis information from the CHNS was limited and not coded into the ICD-9-CM system. Second, even if we could classify individuals into ADGs, the healthcare spending patterns are not comparable between China and the United States. However, it is possible to specify a risk-adjustment model by following the insight of the ACG method. The first step is to classify CHNS disease history into four disease groups (semi-ADGs; Table 2).

[Table 2 to be here]

Then, we specify a risk-adjustment model as follows:

$$m_i = \sum_s m_{is} = \gamma_0 + \gamma_1 d_{>65} + \gamma_2 male + \gamma_3 d_{>65} * male + \gamma_4 disable \tag{15}$$

$$+ \gamma_5 d_{>65} * disable + \boldsymbol{\gamma_6 DG} + \boldsymbol{\gamma_7 M} + \boldsymbol{\gamma_8 R} + \nu_i$$

Individuals' total NCMS benefits are regressed on indicators of years over 65 ($d_{>65}$), being a male ($male$), disability status ($disable$), and their interaction terms. The risk-adjustment model also controls for indicators of disease groups ($\boldsymbol{DG}$), months ($\boldsymbol{M}$), and regions ($\boldsymbol{R}$). The ACG risk premium is set as predict annual NCMS benefit[5].

5. Results and Discussion

5.1 Population Characteristics

Table 3 reports population health status and benefit distributions. For self-reported health status, residents in East Coast region are most likely to report suffering from chronic diseases, and residents in Western China are least likely. Surprisingly, Northeast residents tend to be

[5] Since the NCMS benefit is only reported for the past four weeks, we predict a counterfactual m_i at these months not covered by the survey period. For the month when m_i is reported, we keep the original values. are summed up to an annual benefit. An individual's annual NCMS benefit is a sum of monthly predicted m_i.

sickest and have high percentages of high blood pressure, obesity, or disability, even though the sample from the Northeast has the lowest average age of all the regions. The Western region again has the lowest rate of the unhealthy population based on physical examination results, which was 24% in 2011.

Next, we calculate median insurance benefits of the healthy and unhealthy groups classified by self-reported indicators[6] and construct $\underline{\theta_s}$ and $\overline{\theta_s}$ based on equation (13). The parameter $\Delta\theta_s = \overline{\theta_s} - \underline{\theta_s}$ is calculated under two scenarios: 1) when governments can predict 2011 NCMS benefits with the more-information set and 2) when they can predict with less information. First, we do not find a substantial group difference in insurance benefits for preventive health services. The government anticipates that healthy people demand slightly more preventive health services than unhealthy people under the less-information set. Second, the discrepancy of benefit ($\Delta\theta$) for inpatient treatments is approximately twice of that for outpatient treatments, that is, inpatient benefits are heavily used by unhealthy households than the other group. Third, the government expects a larger difference in insurance benefits between the two groups as it has more information to predict household spending.

[Table 3 to be here]

5.2. Selection Index

Next, we examine service-level spending characteristics by region. According to equation (10), we calculate components of selection indices[7] under the current NCMS risk premium. As shown in Table 4, the normalized average plan revenues (C) are negative in all regions. This

[6] We also calculated $\underline{\theta_s}$ and $\overline{\theta_s}$ based on exam-based indicators, and the differences in median benefits between two groups are minimal, so we focus on self-reported health status in following analyses.
[7] One problem is that the demand elasticities of different services are unknown, so we follow the practice of Ellis, R.P., McGuire, T.G., 2007. Predictability and predictiveness in health care spending. Journal of health economics 26, 25-48. and assume all elasticities equal to -1.

finding is consistent with studies by Zhang et al. (2010b) and Brown et al. (2009), which have suggested that the NCMS faced risks of budget deficits. In reality, local governments may finance the NCMS program through state-owned companies or use the reserve funds saved in previous years, but the possibility of fund deficits can be a substantial pressure for poorer counties (Zhang et al., 2010a).

The selection indices tend to increase when the government has more information to predict households' insurance benefits. For example, $cov(\widehat{m}_{is})$ captures the variations in predicted benefits: the more predictable the spending on a health service, the larger the $cov(\widehat{m}_{is})$. We find spending on preventive services varies the most, especially when the government is more informed. Under the current fixed risk premium, inpatient reimbursements are highly correlated with plan costs because the NCMS focused on covering inpatient treatments. As a result, the selection indices are high, that is, the local government has a strong incentive to ration the NCMS benefit on this type of service. Outpatient serves are moderately predictable but less correlated with plan profits; thus, the government has less incentive to ration outpatient services than inpatient services. Although the relative magnitudes of selection indices are consistent, we discover substantial variations between regions. For example, the East Coast region's selection index on inpatient services is very high, because this service is very predictable and highly correlated with plan costs. This result is consistent with our summary statistics, showing that the average reimbursement rate for the East Coast is lowest for inpatient services.

[Table 4 to be here]

5.3. Relative Shadow Prices

After examining regional population health status and service characteristics, we report the second-best shadow prices calculated according to equation (12). To reveal service-level distortions, we normalize the shadow prices of preventive services to one in each region; thus, all other shadow prices are relative to this category. Preventive service is chosen as the baseline because our previous analyses suggest that the government has little incentive to distort this service. If there is little service-level distortion, we should expect all shadow prices close to 1.

Under the actual NCMS risk premium of RMB 230 in 2011, all calculated shadow prices are negative due to negative predicted plan profit in our sample. By following Frank et al. (2000), we adjust the risk premium upward until all shadow prices in a region become positive and report the minimum adjustments in Table 5. We find it is easiest to achieve break-even for the East Coast region because their NCMS benefit plans are the least generous. The risk premium must be adjusted upward by RMB 950 in the Northeast region to obtain positive shadow prices. According to the summary statistics, this is perhaps because the Northeast region has a much higher percentage of the unhealthy population. Even with lump-sum adjustments in each region, the shadow prices of inpatient services are much higher in the Northeast ($p_s = 197$) and Western ($p_s = 51$) regions. In these two regions, the local governments undercover inpatient services when they have less information to predict household spending. One potential reason for this phenomenon is that county governments in Western China are poorer (Xinqiao, 2003). To conserve funds, less-informed county governments in Western China must restrict NCMS coverage for inpatient treatments due to a small budget. The distortions of service-level coverages are reduced as the local governments have more information to predict household spending.

[Table 5 to be here]

How do shadow prices change if the government can adjust risk premium based on prior program costs? To illustrate this scenario, we set the risk premium as the sample average insurance benefit in 2009 and calculate shadow prices in 2011. Although shadow prices in most cases are closer to 1, Northeast China still has negative shadow prices, meaning that the NCMS loses money on these services even if its risk premium is adjusted by prior cost information. ACG risk adjustment performs better than the second risk-adjusted premium to reduce service-level distortion by considering individual characteristics and past disease history, even though it still does not fix negative shadow prices in Northeast region.

However, the relative shadow prices in Table 5 are not comparable between regions because they are relative to the shadow prices of preventive services, which are different in each region. Another notable investigation would be to examine the equity of service coverage between regions. In Table 6, we normalize Central China's shadow prices to be one and calculate relative shadow prices. Again, the actual NCMS premium is adjusted upward to obtain positive shadow prices. In a comparison between regions, we find that although the Northeast region has the highest risk of fund deficits with actual NCMS risk premium, it will be most generous regarding covering health services if this region is subsidized by a minimum lump-sum adjustment and the local government is more-informed.

If the NCMS program is allowed to set risk premium based on prior average costs, we find the Northeast and Western regions have much higher shadow prices compared with other regions, that is, county governments in these regions have strong incentives to restrict benefits. ACG risk adjustment is helpful to reduce service-level distortion within a region, but still cannot address the inequity of insurance benefits between regions.

[Table 6 to be here]

6. Conclusion

This study investigates service-level coverages of the NCMS program and makes three contributions to the literature. First, we develop a theoretical framework to show how population health status and health service characteristics affect local governments' selective incentives. Second, using the 2009 and 2011 CHNS data, we reveal service-level distortions in different regions of China and show how governments behave under different information assumptions. Third, different risk-adjustment systems are explored to provide additional details on how to improve the efficiency in NCMS benefit designs and financial sustainability.

Results suggest that average annual insurance benefit from the NCMS program exceeded the actual risk premium collected by the program, which led to negative shadow prices. This finding revealed challenges of financial sustainability faced by the NCMS program and may explain its discontinuity. Although the NCMS program was merged with URRMI in 2018, we suspect similar problems persist in the new health program if governments' cost-control incentives are not appropriately addressed. The empirical results from CHNS data supported our theoretical implications: the NCMS plan tends to undercover the services that are predictable and negatively correlated with plan profits, such as inpatient treatments. Although the primary objective of the NCMS was to reduce medical impoverishment, our results suggested local governments in the sickest or poorest areas may have a strong incentive to ration services demanded more by unhealthy people. This finding may explain why the NCMS failed to provide financial protection to the rural population in the short run, even with high participation rates.

In addition to a minimum lump-sum adjustment on the actual NCMS risk premium, we evaluated two alternative risk-adjustment methods. One risk premium was the flat-rate but adjusted by previous total NCMS cost, and the other was the ACG risk premium adjusted by individual characteristics and disease history. The second risk premium was more effective in reducing service-level distortions within a region, but not in reducing the inequality of service coverages between regions. This finding revealed the trade-off between service-level efficiency and equity of coverage between regions.

If the goal is to allocate the NCMS benefits more efficiently between services, risk premiums should be adjusted by individual characteristics and diseases history to reduce local governments' incentive to engage in "indirect selection." However, this strategy has higher fees for people living in Northeast and Western China, which may increase inequity in health coverage between regions. Additionally, the ACG risk premium may increase the cost of implementing the NCMS and cause ethical debates about whether to charge people who are the sickest higher risk premiums.

This study has limitations that suggest directions for future research. First, health spending data were reported for only the past 4 weeks; thus, we may have introduced measurement errors when predicting individuals' monthly health spending and summing them up to annual spending. Second, types of health services reported in the CHNS survey were very rough. Detailed classification of health services is required to provide more insights into the NCMS benefits designs. Researchers may consider using claims data from the NCMS information system if they can access this information. Third, the assumption of profit-maximizing may not represent the real objective of local governments well. Future steps should be taken to modify the objective function and better capture governments' incentives. Additionally, this study treated a household as a single agent. This assumption may be relaxed in future studies to consider potential a conflict of interest between family members. Finally, due to the small sample size, we could not run separate empirical models by region; thus, we added regional dummies to capture the heterogeneity in health spending between regions. This model specification may underestimate regional variations. If the sample size is sufficiently large, separated regressions in each region are more appropriate. Nevertheless, the general conclusion of this study still stands: in those poor regions with a higher portion of unhealthy residents, local governments have incentives to undercover the health services that residents who are sicker demand most, and appropriate risk adjustments are required to reduce the distortions.

Tables

Table 1 Summary statistics for variables in 2011, individual-level

Region		Northeast	Central	Western	East Coast	p-value
Number of Observations		1729	239	2563	1077	
Health Spending (RMB) in the past 4 weeks						
Self-treat& family practice	Mean	12.21	13.62	23.69	9.05	0.282
	Std. Dev.	194.07	256.36	259.59	97.97	
Inpatient services	Mean	92.41	95.17	77.33	44.28	0.815
	Std. Dev.	1564.42	1814.32	1405.77	653.57	
Outpatient services	Mean	61.69	88	46.69	58.22	0.485
	Std. Dev.	950.99	1393.71	391.09	445.27	
Preventive services	Mean	1.21	1.82	1.73	0.53	0.406
	Std. Dev.	18.93	28.38	23.28	10.98	
Total health spending	Mean	164.23	193.66	142.58	108.22	0.566
	Std. Dev.	1828.78	2283.16	1463.42	783.04	
% covered by insurance						
Inpatient services	Mean	47.5	55.36	37.15	33.36	0.062
	Std. Dev.	30.16	18.01	14.01	18.67	
Outpatient services	Mean	7.81	28.47	26.67	30.04	0.004
	Std. Dev.	20.89	34.66	22.31	13.92	
Preventive services	Mean	4.65	15.86	7.27	2.89	0.013
	Std. Dev.	21.31	34.66	22.31	13.92	
benefit of NCMS (RMB) in the past 4 weeks						
Total benefit	Mean	54.07	79.55	38.81	24.02	0.225
	Std. Dev.	729.44	1189.87	666.03	265.42	
Demographic characteristics						
Age	Mean	30.94	45.64	43.75	49.73	<0.001
	Std. Dev.	24.61	19.05	20.81	17.76	
Gender	Mean	0.52	0.55	0.52	0.56	0.103
	Std. Dev.	0.5	0.5	0.5	0.5	
Years of education	Mean	6.79	6.56	5.76	5.88	<0.001
	Std. Dev.	3.16	4.04	3.85	4.12	
Total net household income	Mean	38732.75	33521.2	32142.02	46066.28	<0.001
	Std. Dev.	42325.19	47772.18	31871.43	47186.33	

Table 2 Classification of CHNS disease history

Semi-ADG	Description	Examples of CHNS recorded diseases
DG1	Time-limited, major	myocardial infarction, stroke
DG2	Chronical medical	high blood pressure, diabetes
DG3	Malignancy	all types of cancers
DG4	Others	asthma, bone fracture

Table 3. Benefit distribution between healthy and unhealthy households

	Less-information set				More-information set			
Type of services	Northeast	Central	Western	East Coast	Northeast	Central	Western	East Coast
Percent of the unhealthy population (λ)								
Self-reported	0.11	0.14	0.1	0.21				
Exam-based	0.57	0.35	0.24	0.36				
Discrepancy in insurance benefit ($\Delta\theta_s = \overline{\theta_s} - \underline{\theta_s}$)								
Preventive Services	-0.04	-0.05	-0.04	-0.04	0.08	0.08	0.08	0.09
Inpatient costs	0.44	0.44	0.44	0.45	0.51	0.53	0.52	0.52
Outpatient costs	0.21	0.19	0.19	0.20	0.23	0.21	0.25	0.25

Table 4 Estimated selection index under the current NCMS risk system and two information sets.

Region	Statistics	Northeast	Central	Western	East Coast
Less-information set					
Normalized plan profit	$(\bar{\pi}-1)/\sigma_\pi$	-0.94	-0.51	-0.62	-0.06
Preventive services	$cov(\widehat{m}_{is})$	1.07	1.07	1.07	1.07
	ρ_{m_{is},π_i}	-0.15	-0.19	-0.13	-0.14
	I_s	1.10	0.71	0.75	0.21
Inpatient costs	$cov(\widehat{m}_{is})$	0.91	0.93	0.93	0.94
	ρ_{m_{is},π_i}	-0.99	-0.91	-0.96	-0.82
	I_s	1.84	1.36	1.51	0.83
Outpatient costs	$cov(\widehat{m}_{is})$	1.00	0.99	0.98	0.99
	ρ_{m_{is},π_i}	-0.40	-0.51	-0.38	-0.47
	I_s	1.34	1.02	0.99	0.53
More-information set					
Normalized plan profit	$(\bar{\pi}-1)/\sigma_\pi$	-0.22	-0.19	-0.15	-0.05
Preventive services	$cov(\widehat{m}_{is})$	12.46	12.65	12.70	11.26
	ρ_{m_{is},π_i}	-0.04	-0.06	-0.23	-0.06
	I_s	0.77	0.97	3.12	0.69
Inpatient costs	$cov(\widehat{m}_{is})$	3.74	4.01	3.95	5.46
	ρ_{m_{is},π_i}	-0.96	-0.88	-0.94	-0.83
	I_s	3.81	3.73	3.85	4.57
Outpatient costs	$cov(\widehat{m}_{is})$	7.12	5.10	8.30	5.91
	ρ_{m_{is},π_i}	-0.28	-0.47	-0.25	-0.55
	I_s	2.22	2.56	2.22	3.33

Table 5. Service-level relative shadow prices under two information sets and risk-adjustment systems by region[a]

Type of services	Mini. Adj (RMB)	Less-information set			More-information set		
		Preventive services	Inpatient services	Outpatient services	Preventive services	Inpatient services	Outpatient services
Current NCMS risk premium with adjustments[b]							
Northeast	950.00	1.00	197.80	6.45	1.00	1.11	1.14
Central	270.00	1.00	1.65	1.86	1.00	1.63	9.29
Western	420.00	1.00	51.02	5.29	1.00	1.18	1.15
East Coast	30.00	1.00	3.45	6.46	1.00	0.89	1.62
Risk premium adjusted by the regional mean benefit in 2009[c]							
Northeast		(-)	(-)	(-)	1.00	2.65	2.22
Central		1.00	1.09	1.11	1.00	1.00	1.07
Western		1.00	1.69	1.53	1.00	1.08	1.08
East Coast		1.00	1.16	1.22	1.00	0.96	1.11
Risk premium adjusted by disease groups and disability status[c]							
Northeast		(-)	(-)	(-)	1.00	1.05	1.09
Central		1.00	0.90	1.05	1.00	0.93	1.07
Western		1.00	1.06	1.43	1.00	0.94	0.90
East Coast		1.00	0.91	1.14	1.00	0.97	1.21

Note: [a]All shadow prices are relative to the category of preventive services; thus, the shadow prices for the category of preventive services are normalized to 1.00 in all cases.

[b]2011 NCMS risk premium was adjusted upward with a minimum amount to obtain positive shadow prices, and the minimum amounts are reported.

[c] (-) indicates the estimated shadow price is negative.

Table 6. Between-region relative shadow prices under two information sets and risk-adjustment systems by service[a].

	Less-information set				More-information set			
Type of services	Central	Northeast	Western	East Coast	Central	Northeast	Western	East Coast
	Current NCMS risk premium with adjustment							
Preventive	1.00	0.73	1.70	3.10	1.00	0.10	0.36	0.88
Inpatient costs	1.00	87.89	52.64	6.48	1.00	0.07	0.26	0.48
Outpatient costs	1.00	2.54	4.84	10.76	1.00	0.01	0.04	0.15
	Risk premium adjusted by the regional mean benefit in 2009[b]							
Preventive	1.00	(-)	7.35	4.81	1.00	15.03	5.23	4.33
Inpatient costs	1.00	(-)	11.43	5.14	1.00	39.94	5.66	4.15
Outpatient costs	1.00	(-)	10.14	5.26	1.00	31.22	5.31	4.49
	Risk premium adjusted by disease groups and disability status[b]							
Preventive	1.00	(-)	6.19	3.56	1.00	2.23	3.54	2.73
Inpatient costs	1.00	(-)	7.32	3.60	1.00	2.52	3.61	2.85
Outpatient costs	1.00	(-)	8.43	3.88	1.00	2.26	2.97	3.07

Note: [a]All shadow prices are relative to those prices in Central China; thus, the shadow prices in Central China are normalized to 1.00 in all cases. 2011 NCMS risk premium was adjusted upward to obtain positive shadow price.

[b] (-) indicates the estimated shadow price is negative.

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Appendix

Appendix A Derivation of the selection index

Given $\mathrm{I_s} = \frac{d\pi}{dp_s} \times \frac{1}{N\bar{m}_s\sigma_\pi}$, $\bar{m}_s = \frac{1}{N}\sum_i n_i\widehat{m}_{is}$

The first part of $\mathrm{I_s}$ can be written as

$$\frac{d\pi}{dp_s} = \sum_i [\frac{dn_i}{dp_s} \cdot \pi_i - n_i\widehat{m}'_{is}], \quad where\ \pi_i = r_i - \sum_s \widehat{m}_{is} \tag{A1}$$

According to Equations (4) and (5),

$$\frac{dn_i}{dp_s} = \frac{dn_i}{dv_i} \cdot \frac{dv_i}{d\widehat{m}_{is}} \cdot \frac{d\widehat{m}_{is}}{dp_s} = \mathrm{F}'_i p_s\widehat{m}'_{is}$$

Let the elasticity of service s be $e_s = \frac{p_s}{\widehat{m}_{is}} \cdot \widehat{m}'_{is}$, and therefore $\widehat{m}'_{is} = e_s \cdot \widehat{m}_{is}/p_S$. Plug it to equation (A1)

$$\frac{d\pi}{dp_s} = e_s\sum_i \mathrm{F}'_i\widehat{m}_{is} \cdot \pi_i - \frac{e_s}{p_s}\sum_i n_i \cdot \widehat{m}_{is} = e_s\sum_i \mathrm{F}'_i\widehat{m}_{is} \cdot \pi_i - \frac{e_sN\bar{m}_s}{p_s}$$

We assume $F'_i = 1$ and denote the correlation coefficient between $\widehat{m}_{is}$ and π_i as

$\rho_{\mathrm{m_{is}},\pi_i} = \frac{1}{N\hat{\sigma}_s\sigma_\pi}\sum_i(\widehat{m}_{is} - \bar{m}_s)(\pi_i - \bar{\pi}) = \frac{\sum_i(\widehat{m}_{is}\pi_i) - N\bar{\pi}\bar{m}_s}{N\hat{\sigma}_s\sigma_\pi}$, where $\bar{\pi} = \frac{1}{N}\sum_i n_i\pi_i$

Substitute out $\sum_i \widehat{m}_{is} \cdot \pi_i$ using the above equation

$\frac{d\pi}{dp_s} = e_s \cdot (\rho_{\mathrm{m_{is}},\pi_i} \cdot N\hat{\sigma}_s\sigma_\pi + N\bar{\pi}\bar{m}_s - \frac{N\bar{m}_s}{p_s})$

When evaluated at $\mathrm{p}_s = 1$, the selection index became

$$\mathrm{I_s} = \frac{d\pi}{dp_s} \times \frac{1}{N\bar{m}_s\sigma_\pi} = e_s \cdot (\rho_{\mathrm{m_{is}},\pi_i} \cdot \hat{\sigma}_s/\bar{m}_s + \frac{\bar{\pi} - 1}{\sigma_\pi}) = e_s \cdot [\rho_{\mathrm{m_{is}},\pi_i} \cdot cov(\widehat{m}_{is}) + C]$$

Appendix B Calculate shadow prices with government uncertainty

$$\max_{\boldsymbol{p}} \pi(\boldsymbol{p}) = \sum_i n_i \left[\widehat{m_\iota(\boldsymbol{p})}, \hat{u}_i^0, c_i\right] \cdot \left[r_i - \sum_s \widehat{m_{\iota s}(p_s)}\right]$$

$=\sum_i n_i \, [[\Theta_1 m_{i1}^B(p_1), \Theta_2 m_{i2}^B(p_2), \dots, \Theta_S m_{iS}^B(p_S)], \hat{u}_i^0, c_i] \cdot [r_i - \sum_s \Theta_s m_{is}^B(p_s)]$

Again, take the first order condition.

$$\frac{d\pi}{dp_s} = \sum_i [\frac{dn_i}{dp_s} \cdot (r_i - \sum_s \Theta_s m_{is}^B) - \Theta_s n_i m_{is}^{B\prime}] = 0$$

According to Equations (4) and (11), we have $n_i\left[\widehat{m_\iota(\boldsymbol{p})}, \hat{u}_i^0, c_i\right] = 1 - \mathrm{F}[\hat{u}_i^0 + c_i - \sum_s v_{is}(\Theta_S m_{is}^B)]$ and assume $v_{is}(.)$ is independent of other services $s' \neq s$.

$$\frac{dn_i}{dp_s} = \frac{dn_i}{dv_{iS}} \cdot \frac{dv_{is}}{d\Theta_s m_{is}^B} \cdot \frac{d\Theta_s m_{is}^B}{dp_s} = \mathrm{F}_i' p_s \Theta_s m_{is}^{B\prime}$$

Let the baseline elasticity of service s be $e^s = \frac{p_s}{m_{is}^B} \cdot m_{is}^{B\prime}$, and therefore $m_{is}^{B\prime} = e_s \cdot m_{is}^B / p_S$. Then $\frac{dn_i}{dp_s} = \mathrm{F}_i' \Theta_s e_s m_{is}^B$. Plug it into the first order condition

$$\frac{d\pi}{dp_s} = \sum_i [\mathrm{F}_i' \Theta_s e_s m_{is}^B \cdot (r_i - \sum_s \Theta_s m_{is}^B) - \frac{\Theta_s n_i e_s m_{is}^B}{p_s}] = 0$$

Given p_s, Θ_s and e_s are the same for all households. We multiply both sides by $\frac{p_s}{e_s \Theta_s}$, and the first order condition becomes

$$p_s \sum_i \mathrm{F}_i' m_{is}^B \cdot (r_i - \sum_s \Theta_s m_{is}^B) - \sum_i n_i m_{is}^B = 0$$

So, the profit-maximizing shadow price in the second-best case is $p_S^{second} = \frac{\sum_i n_i m_{is}^B}{\sum_i \mathrm{F}_i' m_{is}^B \cdot (r_i - \sum_s \Theta_s m_{is}^B)}$