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DOES HEALTH INSURANCE COVERAGE LEAD TO BETTER HEALTH AND EDUCATIONAL OUTCOMES? EVIDENCE FROM RURAL CHINA

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ABSTRACT

Many governments advocate nationwide health insurance coverage but the effects of such a program are less known in developing countries. We use part of the 2006 China Agricultural Census (CAC) to examine whether the recent health insurance coverage in rural China has affected children mortality, pregnancy mortality, and the school enrollment of the 6-16 year old. Our data represent a census of 5.9 million people living in eight low-income rural counties, four of which have adopted the New Cooperative Medical System (NCMS) by 2006 and the other four did not adopt NCMS until 2007. In the counties that offer NCMS, a household may take or not take the insurance.

A first look of the data suggests that enrolling in NCMS is associated with better school enrollment and lower mortality of young children and pregnant women. However, using a difference-in-difference propensity score method, we find most of these differences are driven by the endogenous introduction and take up of NCMS, and classical propensity score matching fails to address the selection bias. While NCMS does not show beneficial impacts on the average population, we find some evidence that NCMS helps improve the school enrollment of six-year-olds.

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1. Introduction

Many governments advocate nation wide health insurance in order to improve access to health care and ease the burden of health cost on individual households. While the expansion of health insurance coverage has been shown to improve health and educational outcomes in the US[2], the role of health insurance can be different in a developing country. On the one hand, the benefits of government-subsidized health insurance could be more prominent when a large portion of population is poor and faces a high ratio of health care cost to income. On the other hand, if health insurance offers limited reimbursement, better access to health care does not necessarily ease the financial burden of health cost; a household may spend even more out of pocket when they are more willing to seek treatment. In addition, the health care delivery system is likely under-developed in a poor area and the administrative cost of health insurance can be high due to inefficient management and dispersed population. These factors further limit the potential benefits of health insurance coverage. Which force dominates is an empirical question.[3]

In this paper, we use China's New Cooperative Medical System (NCMS) to quantify the effect of health insurance on children mortality, pregnancy mortality, and school enrollment. Despite the fast economic growth in the past 20 years, China shows an uneven

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[2] The expansion of Medicaid coverage has been shown to improve mother's prenatal care, reduce infant mortality, reduce the incidence of low birth weight and reduce hospitalization (Currie and Gruber 1996a, 1996b, Dafny and Gruber 2005). The introduction of the State Children's Health Insurance Program (SCHIP) has been linked to a greater health insurance coverage, better children health and better school performance (LoSasso and Buchmueller 2004, Joyce and Racine 2003; Levine and Schanzenbach 2009). See the review of Levy and Meltzer (2008) for more details.

[3] Wang et al. (2009) summarizes the mixed evidence of the impact of health insurance in developing countries such as Iran (Russell 2005), Brazil (Nyman and Barleen 2005), Vietnam (Wagstaff and Pradhan 2005), and China (Wagstaff and Yu 2007 on the World Bank Health VIII Project).

progress against poverty (Ravallion and Chen 2007). In 2005, China still has 208 million people living below the World Bank's $1.25-per-day poverty line (Chen and Ravallion 2008)[4], most of them are rural. According to the 2007 National Statistical Yearbook, rural residents on average spend 5.34% of income on health care and the ratio increases to 10% for the poorest twenty percent. These numbers tend to underestimate the financial burden of health care cost, because poor households may choose no treatment due to high treatment cost. Researchers have documented a sizable health-expenditure disparity between urban and rural areas, largely due to the increasing gaps in income, health care utilization and local government budget deficit (Liu et al. 1999; Chou and Wang 2009).

To address the lack of health insurance in rural areas[5], China initiated the NCMS in 2003 as a co-pay insurance system, targeting rural residents with heavy subsidy from both central and local governments. Unlike the mandatory insurance program proposed in the recent US health care reform, NCMS is implemented county-by-county, allowing local governments to decide when to introduce NCMS, how much premium to charge, and how many benefits to offer. If the county offers NCMS, a rural household can choose to enroll in the NCMS for either every household member or none of them. The diffusion of NCMS is quick: 14% of counties offered NCMS in 2004 ((MOH 2005); by June 30, 2008, every county offers NCMS, covering 91.54% of the rural population.[6]

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[4] This number increases to 473.7 million if the poverty line is increased to $2 per day (Chen and Ravallion 2008).

[5] The old community-based health insurance system broke down when the rural economy shifted away from the collective system in 1978 (Hsiao 1984). As a result, patients face increased financial burden, reduced access to health care services, and compromised service quality (MOH 1999).

[6] New release from Guang Ming Daily, written by Ying Zhang, October 22, 2008, accessed at http://www.hyey.com/Article/zhengcezhuanti/xinnonghe/now/xiyue/200810/141630.html on June 5, 2010.

In theory, health insurance could encourage health care utilization and improve the health of the insured. Whether health insurance relieves the financial burden of health care expenditure on a household depends on the scope of the insurance coverage and the extent to which better health leads to better labor productivity and better income. Earlier studies find mixed results on the impact of NCMS. Some show that NCMS reduces illness-related poverty (Chen et al. 2005) and increases the rate of hospitalization (Yuan et al. 2006), while others are concerned of the low reimbursement rate (Zhang et al. 2006, Yi et al. 2009) and the lack of evidence in health care utilization and health improvement (Lei and Lin 2009).

This paper aims to provide additional evidence regarding the impact of NCMS on young children mortality, pregnancy mortality, and children schooling. The potential impact could come from more health care utilization, better health status and the relief of financial burden from health care. We use a large cross-section from the 2006 China Agriculture Census. Although the data do not track individuals before and after the introduction of NCMS, they cover a continuous area in a poor inland province including four counties that have introduced NCMS at the time of survey (end of 2006) and four counties that did not introduce NCMS until 2007. The eight counties are geographically next to each other and belong to the same administrative district, hence similar in demographics, access to health care services, and access to public education. Because the data were collected as part of the census, we observe a large sample including 5.9 million individuals, 1.4 million households, and 1.4 million school age children across 3,977 villages[7]. The large sample size helps

This article cites data source from the Ministry of Health.

[7] There are actually 3,986 villages in the whole data but 9 villages do not provide any village-level information. We delete them from analysis.

capture severe health risks, which by definition are small probability events but could have catastrophic impact on a rural household without health insurance. High poverty in this area also makes it attractive for identifying the impact of NCMS on a financially vulnerable population.

A simple comparison of insured and uninsured households shows significantly better mortality and schooling outcomes in the insured households. However, this comparison can be biased due to the endogenous introduction and take up of NCMS. If NCMS counties are richer and enjoy better fiscal conditions, the population in the NCMS counties could have better health and educational outcomes even without NCMS. Even if the two types of counties are comparable, richer and more health-conscious households are more likely to take up the insurance and therefore generate another selection bias.

To address the selection bias, we propose a difference-in-difference (DID) propensity score comparison between NCMS and non-NCMS counties. Classical propensity score matching focuses on a treatment program (i.e. NCMS counties in our context), assuming that treated and untreated individuals are similar in unobservables if they are matched in observables (Rosenbaum and Rubin, 1983). This assumption is relaxed when we extend propensity score to all counties and use households in the non-NCMS counties as control for similar households in the NCMS counties. The rich heterogeneity within a county allows us to further control for the unobservable county attributes thus accounting for the endogenous introduction of NCMS county by county. Our method is similar to the DID matching strategy proposed by Heckman, Ichimura and Todd (1997) and Heckman, Ichimura, Smith and Todd (1998). The main difference is that they use longitudinal data (or repeated cross-sections) to difference out time-invariant factors before and after a treatment program[8], while we take advantage of the similarity between NCMS and non-NCMS counties and use households in non-NCMS counties as a control group.

Results from our DID propensity score method suggest that most of the seemingly beneficial effects of NCMS are driven by selection. The classical propensity score matching fails to address the selection bias, because similarity of observables does not imply similarity of unobservables. Applying the DID propensity score method to population of low- and high-socioeconomic status separately, we find that NCMS may have moderate effects in improving the school enrollment of six-year-olds.

The rest of the paper is organized as follows. Section 2 describes the data and the background of NCMS in the studied area. Section 3 presents data summary and OLS regressions on the key outcomes. Section 4 specifies our DID propensity score methodology and compares it to the classical propensity score matching. Section 5 reports the main results. Section 6 offers a brief discussion and conclusion.

2. Background and Data

The National Bureau of Statistics of China has organized local governments to conduct two rounds of the China Agricultural Census (CAC) in 1996 and 2006 respectively. Drawing from the 2006 CAC, our data cover all the residents residing or having registered residence in a continuous

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[8] Using Longitudinal data that track program participants and non-participants before and after a treatment program, Smith and Todd (2005) show that DID matching estimators perform much better than classical cross-sectional matching when participants and non-participants are drawn from different regional labor markets and/or were given different survey questionnaires.

area as of December 31, 2006. Due to data confidentiality, we are not allowed to reveal the geographic location, but we can assure readers that the studied area is mostly rural, belongs to an inland province, and has a per capita income below the national average. In total, we observe 5.9 million individuals in 1.4 million households and 3,977 villages. These villages spread across 250 townships in 8 counties, of which one county adopted NCMS since 2004 (refereed to as county A), three counties adopted NCMS in 2006 (refereed to as B, C, D), and the other four did not adopt NCMS until 2007 (refereed to as E, F, G, H). The size of the whole census area is roughly 16,000 km^2 total, with on average area of 4 km^2 per village. More details of this data set are available in Chen, Jin and Yue (2010).

In 2006, each NCMS participating individual had on average 50 RMB[9] in the NCMS system, of which 10 RMB was paid by the individual, 20 RMB was subsidized by the central government and the other 20 RMB were contributed by the county government. This structure remained unchanged in 2007 and 2008[10], but both the central and local government subsidies increased from 20 to 40 RMB per person in 2009. To ensure appropriate use of the NCMS funds, the central government requires local governments to devote the NCMS funds to reimbursement and fund management. Local governments are also required to post a list of existing claims and reimbursements within each village, so that both participating and non-participating villagers have a good idea of how much reimbursement can be obtained from the NCMS if they participate.

In our study area, NCMS pays the insured amount directly if the treatment is delivered at a county- or town-level hospital. If health services are delivered at an above-county hospital, NCMS

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[9] The exchange rate between the Chinese currency (RMB) and US dollar is roughly seven RMB for one dollar.

[10] One exception is that that the individual premium of county E was 12 instead of 10 RMB in 2007. County E reduced this number to 10 RMB in 2008.

requires the patient to pay the full amount out of pocket and then seek reimbursement. For simplicity, we refer to both types of NCMS payment as reimbursement. In our sample period, the reimbursement rate is 60-70% for township healthcare providers, 45-55% for county level providers, and 35-40% for out-of-county providers. These rates have increased 5-15% over time because the total subsidy of central and local governments has doubled in 2009. Benefits cover both inpatient and outpatient care but only for designated providers and designated procedures, so the actual reimbursement rate for all diseases could be significantly lower than the above mentioned percentages. Moreover, the reimbursement is capped at 200-300 RMB per individual per year for outpatient care and 10k-25k RMB for inpatient care. As documented in the existing literature, the potential benefit of NCMS in relieving a household's financial burden mostly depends on the extent to which the NCMS covers the inpatient cost.

Since the take up of NCMS is voluntary, not every household decided to participate. In 2006, among the four counties that offered NCMS, 80% of the households have at least one person enrolled in the NCMS. Although the NCMS in principle does not allow partial participation, we observe 13% of the households have partial participation because some household members have migrated out of the area for work and therefore unlikely to enjoy the benefits of NCMS, or some members have non-rural or non-local residential permit (so called hukou) and therefore likely to have insurance coverage somewhere else.

NCMS was offered to the whole area in 2007, with an average take up rate of 86.74% in 2007, 92.64% in 2008 and 93.37% in 2009. In 2007, 39.59% of the participating individuals receive NCMS reimbursement.[11] Conditional on receiving reimbursement, the average reimbursement was 76

[11] Reimbursement data are only available in county aggregate (from the local government reports). This is why

RMB per person and over 250 (0.013%) individuals received more than 10,000 RMB from NCMS. With more government subsidies in 2009, 66.56% of participating individuals received some form of NCMS reimbursement from January to November 2009, with an average reimbursement of 100.65 RMB per person and over 700 (0.019%) individuals receiving more than 10,000 RMB.

Given the fact that the 2005 per capita income in the studied area was between 1500 and 2000 RMB, these numbers suggest that NCMS is unlikely to offer much financial help for a healthy enrollee that only needs outpatient care for minor diseases. However, NCMS could be a significant help if one has a severe chronic disease (say dialysis due to kidney failure) or has encountered a major acute problem during the year. The 35-70% reimbursement rate and the restriction to designated providers and designated procedures imply that individual households still need to pay a large proportion of the health care cost if they have severe diseases and the out-of-pocket health care expenditure could be even higher if NCMS motivates the insured to seek more treatment.

Due to the low probability of severe health events, we need a large sample to capture the events and their potential impact on a household's health- and non-health outcomes. In addition to the large sample size, our sample area is much poorer than the average rural China but the cost of health care is not proportional to household income. If NCMS has any effect in health- and non-health outcomes, they should be likely to show up in our sample. These reasons lead us to believe that our data could provide additional insights on the effect of NCMS as compared to much smaller and probably more national representative samples used

we cannot examine whether NCMS has increased health care utilization at the household or individual level.

in Yi et al. (2009) and Lei and Lin (2009).

The main part of the data was collected at the household level.[12] By this design, we observe detailed household information including how many individuals reside in the household, their relationship to the household head, their age and gender composition, the amount of contract land, the amount of land in use, ownership of housing, the self-estimated value of house(s), ownership of durable goods, the availability of electricity, water and other amenities, whether the household has enrolled in NCMS (for counties A to D), the number of household members that receive government subsidies, and the household engagement in various agricultural activities. The CAC does not collect data on household or personal income.

Individual level data are limited to age, sex, education, employment, occupation, and the number of months away from home for out-of-township employment in 2006. Since a child in the studied area may get married as early as 17 and daughters often leave their own home after marriage, we restrict our child definition to age 0-16.

School age children are defined as anyone between 6 and 16 inclusive. According to the Law of Compulsory Education of China, the parent or legal guardian of a six-year-old (by September 1) is mandated to enroll the child in school; for the areas short of educational resources (like our study area), the compulsory education age could be delayed until seven. In other words, a seven year old in our sample area is required to enroll in school but the enrollment of a six year old can be voluntary. Given the lack of before-school child care services in rural China, a six year old most likely stays at

[12] The household head was asked to enter information for every family member. If a resident was away from home at the time of interview, his/her information was still collected from the household. If the whole household has registered residence in the studied area but was away from home at the time of interview, the village head would fill the form for the household. Please see more detailed description of this data set in Chen, Jin and Yue (2010).

home if he or she is not enrolled in school. Compulsory education is free of tuition but parents need to pay fees for books and in-school activities, which in total is over 200 RMB per child per year. Children from far away families also need to pay in-school boarding and meal, which could bring the total cost of schooling to as high as 500 RMB per year. Many kids from extremely poor families cannot afford boarding and have to walk several hours a day to school with lunch prepared from home. If NCMS eases the financial burden on a household, it could make more resources available to support child schooling. It could also allow poor children to access health care services when they are sick and reduce the potential interruption of schooling due to illness. Note that the question that CAC asked on school enrollment refers to whether a child is currently enrolled in primary or secondary school, not whether a child has attended school in a particular day. In this sense, we can capture the lack of school enrollment due to major health problems but not school absence due to minor diseases.

Supplemental data were collected at the village level including the size of the village in both arable land and registered population, whether the village is a place for minority gathering, the number of health care providers serving within the village, the distance to the nearest bus station, elementary school, secondary school, and hospital[13], access to water, electricity and other amenities, whether the village has a national poverty status (as designated by the Central government), and how many young children (age 0-5) and pregnant women have died during 2006.[14] The data also include several township level variables, including the number and nature of township-village-enterprises, the distance between the township and county center, whether there is a highway exit within the boundary of the township, and registered population of the township.

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[13] The exact question is to the nearest bus/rail/dock station, but there is no railway station or major river in the studied area.

[14] Due to potential measurement errors in the registered population, we calculate the number of adults per village from our study sample and use it to proxy village population.

3. Data summary and OLS regressions

Throughout the sample, 48.64% of the 5.9 million population was offered NCMS in 2006. Conditional on the four counties that offered NCMS, 80% of households have at least one member enrolled in NCMS. Breaking down this number by county, the household take up rate is 75.7% for county A, 83.7% for B, 78% for C and 83.9% for D. Figure 1 plots the household NCMS take up rate by village, which shows a wide range between 0 and 1 but most villages are concentrated between 0.7 and 1.

Table 1 summarizes the village level mortality of young children and pregnant women by NCMS and non-NCMS counties. Within the NCMS counties, we classify villages into two groups, according to whether the village's NCMS take up rate is above or below the median (83.8%). As shown in the first two columns, NCMS counties have lower mortality than non-NCMS counties for both young children and pregnant women. Conditional on the four counties that offered NCMS, villages with higher NCMS take up rate tend to have slightly lower mortality in both absolute count and mortality rate.[15] These comparisons could reflect the beneficial effects of NCMS or a selection bias if richer and healthier counties are more likely to adopt NCMS early or richer and healthier households are more likely to take up NCMS. We will address the selection issue in the next Section.

Table 2 summarizes the percent of school age children enrolled in school by NCMS status. The enrollment rate is almost 4 percentage points higher in the NCMS counties than in the non-NCMS counties (88.09% vs. 84.13%). Within the four NCMS counties, those who are enrolled in

[15] Child mortality rate is computed as the total number of 0-5 year old death divided by the death count plus the total number of 0-5 year old live in our sample. Pregnancy mortality rate is computed as the total number of pregnancy death divided by the death count plus the total number of 18-30 year old women live in our sample.

NCMS are 2.3 percentage points more likely to have their children enrolled in school (88.55% vs. 86.27%). Again, these raw comparisons could be driven by the NCMS or selection. If we check the school enrollment rate by age, the same pattern holds for every age, but the difference is most obvious for ages 6, 7, and 16. One possible explanation is that financial constrained households are more likely to delay the start of child schooling or stop child schooling right after the 9-year compulsory education. To the extent that NCMS improves health and relieves a household's financial burden, it could increase child schooling, especially at the two ends of the school age.

To have a closer look at the county-level selection, Table 3 lists the relative fiscal condition, per capita income, demographics, % of migrating households, house value and contract land for the eight counties in our sample. Fiscal condition and per capita income are derived from the area's statistical year book, the rest is from the CAC data directly. On average, the NCMS counties have relatively more per capita income and more local fiscal income per capita. County D is the richest of the eight, while County A is almost the poorest of the four NCMS counties although it adopts the NCMS first (in 2004). Note that this comparison is relative within the study area. Overall, the study area is quite poor, with 50% of the population living in villages with national poverty status and the percent of school enrollment (84.13%) is way below the national average (>95%).[16]

Table 4 compares the average household, village and town characteristics of (1) the households that participate in the NCMS, (2) the households that choose not to participate NCMS, and (3) the households that live in non-NCMS counties. Overall the three groups are similar, but

[16] In the news conference held by the Ministry of Education on February 28, 2006, Minister ZHOU Ji reported that the nation-wide average enrollment rate of the 9-year compulsory education is over 95%. In particular, the nationwide enrollment rate is 99.15% for elementary school (grade 1-6) and 95% for middle school (grade 7-9). Source: Ministry of Education (http://www.moe.gov.cn/edoas/website18/11/info18511.htm), accessed at June 5, 2010.

households in NCMS counties are slightly more educated, have a slightly small household size, have slightly higher house value, and are slightly less likely to live in villages with national poverty status. Similar difference exists between NCMS participating and non-participating households within the NCMS counties.

Our first attempt to address selection bias is controlling for observables. Denoting cty for county, v for village, h for household, and i for individual, we regress the three main outcomes – village-level young children mortality ($ChildMortality_v$), village level pregnant women mortality ($PregnancyMorality_v$), and individual-level schooling ($InSchool_i$) – on whether the residing county offered NCMS in 2006 ($NCMSoffered_{cty}$) and the extent to which our subjects take up the NCMS (village take up rate $NCMStakeup_v$ or individual take up dummy $NCMStakeup_i$), controlling for a number of village, household and individual attributes. In particular,

(1) $$ChildMortality_v = \alpha^c + \beta_1^c \cdot NCMSoffered_{cty} + \beta_2^c \cdot NCMStakeup_v + \theta^c \cdot X_v + \varepsilon_v^c$$

(2) $$PregnancyMortality_v = \alpha^w + \beta_1^w \cdot NCMSoffered_{cty} + \beta_2^w \cdot NCMStakeup_v + \theta^w \cdot X_v + \varepsilon_v^w$$

(3) $$InSchool_i = \alpha + \gamma_1 \cdot NCMSoffered_{cty} + \gamma_2 \cdot NCMStakeup_i + \lambda_1 \cdot X_i + \lambda_2 \cdot X_h + \lambda_3 \cdot X_v + \varepsilon_i .$$

As shown in Table 1, the distribution of village-level mortality is concentrated in zero and one death. So we define $ChildMortality_v$ as a dummy of having any young child mortality in village v, and $PregnancyMorality_v$ as a dummy of having any pregnancy mortality in village v. In an unreported table, we use mortality rate for both variables and the results are similar.

The village attributes (X_v) includes village population, distance to the nearest bus station, distance to the nearest elementary school, distance to the nearest secondary school, distance to the nearest hospital as well as the village's poverty status and minority gathering status. The household attributes (X_h) includes house value (self-reported), contract land, whether any household member has migrated for job out of the study area, # of 0-5 year old, # of 6-16 year old, # of 17-23 year old, # of 24-44 year old, # 45-59 year old, # of 60+ year old, and an indicator of main source of income. The individual attributes (X_i) includes child age, gender, and birth order. If NCMS is effective in improving health and reducing the financial burden of health care, we expect $\{\beta_1^c, \beta_2^c, \beta_1^w, \beta_2^w\}$ to be negative and $\{\gamma_1, \gamma_2\}$ to be positive, although all of them can be overestimated due to selection bias.

Table 5 reports the linear-probability OLS results for the two village level dummies of whether there is any mortality in 0-5 year old children and pregnant women. Table 6 reports the linear-probability OLS results for the individual dummy of school enrollment.[17] In both tables, we report one version without county dummies and one version with county dummies. The version without county dummies identifies the coefficient of $NCMSoffered_{cty}$. The other version absorbs $NCMSoffered_{cty}$ in the county dummies and controls for the endogeneity of the NCMS introduction. For school enrollment, we also report results for the full sample of 6-16 year old and the sub sample of 7-15 year old separately.

Both tables confirm the impression from the raw data: NCMS counties have better mortality and schooling outcomes, though the difference on village level mortality is not statistically significant. Conditional on access to NCMS, households enrolling in NCMS are 1.3-1.7% more likely to send their children to regular school, but villages with higher NCMS take up rate does not show significantly better mortality.

[17] We have tried negative binomial for the count of death and probit for in school enrollment. Results are similar.

A typical way to address the endogenous take up of NCMS is to find an instrumental variable that is correlated with an individual household's take up decision but uncorrelated with the household's schooling outcome. Since household is likely the unit of decision for both insurance take-up and schooling, such an instrument is difficult to find. One candidate we have considered is the percent of elderly (age 60+) in other households of the same village. They are likely to affect a household's take up decision because the elderly are vulnerable to health risk and the existing claims and reimbursements are supposedly posted in the village. This positive correlation is confirmed in the data (with a first-stage t-statistics on the instrument equal to 2.35). When we use it as instrument in equation (3), the coefficient of $NCMStakeup_i$ is positive and insignificant with a magnitude roughly 30 times higher than the OLS coefficient.[18] This leads us to conclude that the IV approach is not useful, either because the instrument is weak or is non-valid.

4. Methodology using propensity score

Another method to deal with the selection bias of *NCMStakeup* is propensity score matching. Conditional on the four NCMS counties, the classical propensity score matching will match one NCMS participating household with one non-participating household based on the predicted propensity of take up, and then compare the school enrollment outcome of the two households. Similar matching can be applied to village-level mortality, while the dependent variable of the propensity score prediction is the village-level NCMS take up rate, not the individual decision of whether to enroll in the NCMS.

[18] The 2SLS coefficient of NCMS take up is 0.593 for 6-16 year old and 0.346 for 7-15 year old, conditional on the sample of NCMS counties.

The biggest shortcoming of the classical propensity score matching is that it assumes households (or villages) similar in observables will also be similar in unobservables (Imbens 2004). In particular, assume the outcome of a NCMS participating household i_a (Y_{i_a}) depends on observable attributes ($X_{i_a} = X$) and unobservable attributes (Z_{i_a}). Ideally the average treatment effect (ATT) of enrolling in NCMS should be:

(4) $$ATT_{NCMStakeup=1} = E[Y_{i_a,NCMStakeup=1}(X, Z_{i_a})] - E[Y_{i_a,NCMStakeup=0}(X, Z_{i_a})].$$

However, the non-treatment effect of the treated ($Y_{i_a,NCMStakeup=0}$) is not observed. The classical propensity score matching finds a non-participating household (call it i_b) that has the same observable attributes ($X_{i_b} = X$) and uses this matching household as a control. By this logic, equation (4) can be rewritten as:

(5) $$ATT_{NCMStakeup=1} = E[Y_{i_a,NCMStakeup=1}(X, Z_{i_a})] - E[Y_{i_b,NCMStakeup=0}(X, Z_{i_b})].$$

The underlying assumption is that i_a and i_b are comparable in Z as well. If $Z_{i_b} \neq Z_{i_a}$, the estimated effect suffers from a selection bias.

Intuitively, we should be able to use the extra information in the non-NCMS counties to construct a better comparison group. Let us put aside the county-by-county difference for a while and assume the introduction of NCMS is random. Using the same propensity score function discovered from the NCMS counties, we can predict the propensity score of every household in the non-NCMS counties and then find a matching household in the non-NCMS counties (call it j). The matching implies $X_j = X$. However, since we don't observe whether j would actually take up the NCMS should the NCMS be offered, we don't know j's unobservable attributes (Z_j). The comparison of i_a versus j is still biased if $Z_j \neq Z_i$.

That being said, the presence of non-NCMS counties allows us to adopt a weaker assumption on the unobservables: instead of assuming equal Z conditional on equal X, we can assume the *distribution* of Z conditional on X is the same for the two sets of counties. Under this assumption, we can compare an average household in the NCMS counties (call it i, which by definition includes both i_a and i_b) versus an average household in the NCMS counties (j), conditional on the same X. This way what we identified is the treatment effect of offering NCMS. With the control of the selection bias, the treatment effect of offering NCMS should be equal to the propensity of take-up multiplied by the treatment effect of taking up NCMS. This leads to:

$$
\begin{aligned}
ATT_{NCMSoffered=1} &= prob(takeup \mid x) \cdot ATT_{NCMStakeup=1} \\
&= E[Y_{i,NCMSoffered=1}(X, Z_i)] - E[Y_{j,NCMSoffered=0}(X, Z_j)] \\
&= E[Y_{i,NCMSoffered=1}(X)] - E[Y_{j,NCMSoffered=0}(X)]
\end{aligned}
\tag{6}
$$

where the last equality is achieved by the assumption that Z_i and Z_j conform to the same distribution conditional on X.

Now we consider the fact that the two types of counties are different in unobservable ways as well. A household in a NCMS county may be more likely to enroll its child in school, not because the county offers NCMS but because the county has more resources for public education. If we denote these county unobservables as W_{NCMS} for NCMS counties and

$W_{non-NCMS}$ for non-NCMS counties, the ATT derived by equation (6) is still biased due to $W_{NCMS} \neq W_{non-NCMS}$.

Assuming the county unobservables are the same for every one in the county, we can correct the county-level bias by comparing a group with a high take up propensity (who have observable attributes X^h) and a group with low take up propensity (who have observable attributes X^l) within each type of county. In particular, for the high propensity group, equation (6) is:

$$prob(takeup \mid X^h) \cdot ATT_{NCMStakeup=1} = E[Y_{i,NCMSoffered=1}(X^h, W_{NCMS})] - E[Y_{j,NCMSoffered=0}(X^h, W_{non-NCMS})].$$

For the low propensity group, equation (6) is:

$$prob(takeup \mid X^l) \cdot ATT_{NCMStakeup=1} = E[Y_{i,NCMSoffered=1}(X^l, W_{NCMS})] - E[Y_{j,NCMSoffered=0}(X^l, W_{non-NCMS})].$$

The difference of the two equation yields a DID estimator that can difference out the unobservable county attributes (W) as long as they are the same for both high and low propensity groups within a county. Mathematically,

$$\begin{aligned} DID &= [prob(takeup \mid X^h) - prob(takeup \mid X^l)] \cdot ATT_{NCMStakeup=1} \\ &= \{E[Y_{i,NCMSoffered=1}(X^h, W_{NCMS})] - E[Y_{j,NCMSoffered=0}(X^h, W_{non-NCMS})]\} - \\ &\quad \{E[Y_{i,NCMSoffered=1}(X^l, W_{NCMS})] - E[Y_{j,NCMSoffered=0}(X^l, W_{non-NCMS})]\}. \end{aligned} \tag{7}$$

In other words, if high propensity is 0.95 and low propensity is 0.70, DID identifies the causal effect of randomly increasing NCMS enrollment from 70% to 95%.

Note that our DID estimator utilizes three groups: (1) those who take up NCMS in the NCMS counties, (2) those who do not take up NCMS in the NCMS counties, and (3) those living in the non-NCMS counties. The endogenous individual take up is controlled for by comparing observationally similar households between NCMS and non-NCMS counties, while the endogenous introduction of NCMS at the county level is controlled for by comparing high propensity households and low propensity households within the same type of county.

To summarize, the effectiveness of DID hinges on two assumptions: first, the county-by-county difference applies to every one in the same county equally; second, conditional on observable X, the unobservable individual attributes Z follows the same *distribution* between NCMS and non-NCMS counties, except that the mean of Z could be different given the county-by-county difference. To further clarify, the second assumption does not require the Z distribution to be the same for all kinds of X. Suppose Z represents the unobserved household income and X represents the observed education level of the household head. The second assumption assumes that households with same education level have the same *distribution* of household income, but households with different education may still have very different household income (in both mean and distribution).

We argue that our DID estimator is better than the classical propensity score matching estimator because we do not assume equality in unobservables ($Z_{i_b} = Z_{i_a}$) conditional on equality in observables ($X_{i_b} = X_{i_a}$). One may use propensity score to directly match a NCMS participating household (i_a) to an observationally equivalent household (j) in the non-NCMS counties. For example, Wang et al. (2009) has proposed such a comparison for households taking an experimental health insurance versus households that are not offered such health insurance.[19] This is still biased because i_a is a selected group and the distribution of its unobservables Z_{i_a} could be systematically different from Z_j even if the two sets of counties are overall comparable.

5. Results with propensity score

5.1 Classical propensity score matching results

Table 7 shows the results of the classical propensity score matching, conditional on the four NCMS counties only. In particular, we first use data from the NCMS counties to predict the determination of whether a household has at least one member participating in the

[19] Wang et al. (2009) has data before and after, so their estimate, if translated in our framework, is equivalent to the before-after change of Y for household i_a versus the before-after change of Y for household j.

NCMS. This prediction is not by individual because the CAC reports how many household members enroll in the NCMS but not who has enrolled. Among the 80% households that participate in the NCMS, 13% participate partially due to some household members have non-rural and non-local hukou or have migrated out of the area for work. These factors are controlled for in the propensity score prediction, in addition to household size, education of household head, # of children, # of elderly, contract land, house value and village level variables such as national poverty status, minority gathering status, whether the village is the center of a town, and the village's nearest distance to elementary school, secondary school and hospital.

Once we identify the propensity score function, every participating household is matched with one non-participating household within the four NCMS counties, by both the nearest neighbor and stratification matching. Since the two matching methods yield similar results, we report the nearest neighbor matching. The average treatment effect of NCMS take up on school enrollment is presented in Panel A of Table 7. The result (0.016) is close to that of Table 5 (0.017), suggesting that either there is little selection bias in the OLS results or the classical propensity score matching does not address the selection bias either.

Panel B of Table 7 extends the propensity score prediction to the full sample, and allows a NCMS participating household to be matched with a similar household in a non-NCMS county. As shown in Figure 2, the propensity score distribution is similar across the two types of counties, except that the propensity score of non-NCMS counties has more density in the first (lower) mode and less density in the second (higher) mode. This is consistent with the poorer status of non-NCMS counties as shown in Table 3. Compared to the within-NCMS county matching, the propensity score matching across the two types of counties finds a bigger effect of NCMS take up on school enrollment (0.026 versus 0.016), partly because the across-county comparison includes the fundamental difference between NCMS and non-NCMS counties in the estimate.

We also use the NCMS counties to predict the average take up rate per village as a function of village attributes and extend the prediction to the villages in non-NCMS counties. Since almost all the villages have a positive NCMS take up rate, it is impossible to conduct village-level propensity score matching within the NCMS counties. Panel C of Table 7 presents the propensity score matching results when we match each village in the four NCMS counties with a village in a non-NCMS county. Like the OLS results, we find a negative effect of NCMS take up rate on both types of mortality. However, the effect on whether there is any 0-5 year old death is marginally significant.

5.2 DID estimators

To calculate our DID estimator, we pool the eight counties and divide the overall household-level propensity score distribution equally into 10 bins by the percentile of the distribution.[20] For example, bin 1 refers to the lowest 10 percent of the propensity score distribution, bin 2 refers to the lowest 10-20%, and bin 10 refers to the highest 10%. Using k as the index of bin, we estimate:

$$(8) \qquad InSchool_i = \alpha_k + \beta \cdot X_i + \sum_{cty=1}^{8} \delta_{cty} + \sum_{k=2}^{10} \phi_k \cdot NCMSoffered + \varepsilon_i$$

where $\{\delta_{cty}\}$ are the eight county dummies in an attempt to capture county-by-county

[20] We have tried 20 bins with 5% of data in each bins. Results are very similar.

difference in school enrollment, and $\{\phi_k\}$ is the DID estimator for bin k as compared to bin 1. Since bin 1 has the lowest propensity score, a positive effect of NCMS should be reflected as $\phi_k > 0$ for all $k = 2,3,...10.$ and the magnitude of ϕ_k should increase by k.

Following the same logic, we can conduct the DID estimator at the village level for both types of mortality. Since we have much fewer counts of villages (3977) than individuals (1.4 million), we use 5 instead of 10 bins for the village level estimation:

$$(9) \qquad ChildMortality_v = \alpha_{1k} + \beta_1 \cdot X_v + \sum_{cty=1}^{8} \delta_{1,cty} + \sum_{k=2}^{5} \phi_{1k} \cdot NCMSoffered_{cty} + \varepsilon_{1v}$$

$$(10) \qquad PregnancyMortality_v = \alpha_{2k} + \beta_2 \cdot X_v + \sum_{cty=1}^{8} \delta_{2,cty} + \sum_{k=2}^{5} \phi_{2k} \cdot NCMSoffered_{cty} + \varepsilon_{2v}.$$

In Table 8, we first summarize the distribution of predicted village level NCMS take up rate in the two types of counties. The two distributions are similar in mean, standard deviation, minimum and maximum. Panel B of Table 8 reports the DID estimators for village-level mortalities. Using the lowest 20% villages (in term of predicted take up rate) as the benchmark, we find that all the interactions between bin dummy and *NCMSoffered* are negative but statistically insignificant. This suggests that NCMS has no obvious effect in reducing the incidence of children or pregnancy mortality at the village level, a result consistent with the OLS regression reported in Table 3.

Before we present the DID estimators on individual level school enrollment, Figure 3 plots the average $InSchool_i$ for bins 1-10 in NCMS and non-NCMS counties separately. Within the non-NCMS counties, the average $InSchool_i$ is 85.6% for the 9th bin (top 10-20% of propensity score) and 83.7% for the 1st bin (lowest 0-10% of propensity score). The 1.9% difference filters out the county-level unobservables ($W_{non-NCMS}$) and therefore reflects the fundamental difference between the two bins when there is no NCMS. Similarly, the difference between the 1st and 9th bins is 89.4%-87%=2.4% in the NCMS counties. According to Section 4, the DID estimator can be computed by 2.4%-1.9%=0.5%, which we interpret as the average treatment effect of increasing NCMS take up rate from the propensity of the 1st bin (0.71) to the propensity of the 9th bin (0.872).

Following this logic, equation (8) identifies the DID estimator (ϕ_k) for every bin $k = 2,3,...10$. Compared to Figure 3, equation (8) allows unobservable county attributes to differ among each county and lets $InSchool_i$ to vary by individual attributes such as age, gender and birth order. These individual attributes do not enter into the propensity score prediction because the prediction is done at the household level.

Table 9 reports the DID estimators for bins $k = 2,3,...10$. Unlike the OLS and classical propensity score matching results, these DID estimators are all statistically zero, suggesting that the NCMS has no significant effect on school enrollment once we control for the endogeneous introduction and take up of NCMS.

To make a more straightforward comparison between our DID estimators and the classical propensity score estimate, we add the dummy of *NCMStakeup* to equation (8):

$$(11) \qquad InSchool_i = \alpha_k + \beta \cdot X_i + \sum_{cty=1}^{8} \delta_{cty} + \sum_{k=2}^{10} \rho_k \cdot NCMSoffered + \sum_{k=2}^{10} \mu_k \cdot NCMStakeup + \varepsilon_i .$$

To avoid confusion, we use a different Greek letter for the coefficient of *NCMSoffered* (ρ_k) because the interpretation of this coefficient will be different from that of ϕ_k. Following the notations of Section 4, ϕ_k compares the households of NCMS counties (pooling participants i_a and non-participants i_b) with the households of non-NCMS counties (j) and represent the true causal effect of offering NCMS. In comparison, μ_k captures the difference between i_b

and i_a, which corresponds to the classical propensity score matching results; ρ_k captures the difference between i_b and j; and $\mu_k + \rho_k$ captures the difference between i_a and j. The DID estimator ϕ_k should be somewhere between ρ_k and $\mu_k + \rho_k$.

Table 10 reports the estimates of ρ_k and μ_k for $k = 2,3,...10$. Consistent with the classical propensity score matching results (as reported in Table 7), we find 8 out of the 9 μ_k s are statistically significant. Interestingly, none of the ρ_k s are significant. Comparing Tables 9 and 10, we conclude that most of the observed school enrollment difference between NCMS participating and non-NCMS participating households is due to selection. In other words, the classical propensity score matching estimate (in Table 7) has failed to control the selection bias due to unobservable individual attributes. The propensity score matching between NCMS and non-NCMS counties is even worse because it does not control for the across county difference either.

Is it possible that the NCMS is introduced too soon to have any real effect on school enrollment? The second column of Table 8 compares county A (the one that introduced NCMS in 2004) versus the other four non-NCMS counties. This column shows no positive effect of NCMS either, two of the 8 DID estimators are even negative with 95% confidence.

5.3 DID estimators by different groups

So far we conclude that NCMS has no positive effect on mortality and school enrollment for the average population. One possible explanation for the zero average treatment effect is that NCMS is only effective on a small fraction of population that is most vulnerable to health risk. To examine this explanation, we try to identify the vulnerable population in 7 ways: (1) age 6,7,8, 9-14 and 15-16; (2) boys versus girls; (3) households with and without elderly; (4) households with low and high house value; (5) households with low and high percent of household members being adult labor; and (6) household head with lower- or higher-than median education.

Arguably, younger age children are more vulnerable either because they are more likely to be sick or because the enforcement of compulsory schooling is weaker at younger age (especially 6 year old given the law's permission to delay school start age to seven year old if the area is short of educational resources); girls are more vulnerable because households tend to give priority to boy's education, households with elderly is more subject to the health risk of the elderly; and households with lower house value and/or lower education of household head are more vulnerable because they are likely to be poor. These arguments predict that NCMS may have more beneficial effects on six year olds, girls, and households with any elderly, lower house value and lower household head education. The difference between households with relatively more or less adult labor is less clear: those with less adult labor are more vulnerable to health risk, but those with more adult labor could enjoy a greater gain of the total labor productivity due to health improvement of more labor.

Table 11 reports the DID estimators for child age 6, 7, 8, 9-14 and 15-16 separately. We examine the lower end of the age range in more details because Table 2 shows that ages 6 and 7 have the lowest enrollment rate and the highest variations between NCMS and non-NCMS counties. This leads us to suspect that uninsured households may delay the school starting age of their children due to lack of financial resources for education, lack of access to health care, or both. As we expect, Table 11 shows that NCMS only has some significant effects on the school enrollment of age 6, and close to zero effects on older children. Even for age 6, only 3 out of the 9 interactions of propensity score bin and *NCMSoffered* are statistically significant, suggesting that the effects of NCMS on reducing the delay of elementary school enrollment are moderate and only effective for the households with relatively high propensity scores.[21]

One may argue that parents want to delay child schooling not due to the lack of financial resources but out of the concern that a child younger than the average in his/her class may not have good opportunities to develop leadership and other social skills. We have two reasons to argue against this interpretation. First, if the delay of schooling is due to the concern of social skills, the introduction and take up of NCMS does not affect this concern and therefore should not have any effect on school starting age. Second, Chinese residents that have more financial resources tend to push for early enrollment instead of delayed schooling. For example, in the China Health and Nutrition Survey (CHNS), a longitudinal sample of Chinese households in nine provinces, the six-year-old enrollment rate is significantly higher in urban households (65.1%) than in rural households (56.6%). The comparison is similar if we cut the CHNS sample by whether a household's per capital income is above or below the sample median: the six-year-old enrollment rate is 63.37% in above-median households and 58.36% in below-median households.

In addition, Guo et al. (2007) show that urban China has an alarmingly high rate of caesarean section (c-section) in hospital-based birth (between 26% and 63% during the late 1990s) as compared to the World Health Organization recommended level of 15%. At least

[21] In an unreported table, we repeat the exercise for 16-year-old alone but do not find any significant effect of NCMS on school enrollment.

anecdotally, part of this is attributable to a rush of c-section delivery in urban China towards the end of August because the cutoff for compulsory school enrollment is being six year old by September 1.[22] To address parental cry for early enrollment, the Ministry of Education is considering a proposal that allows five year olds to enroll in the elementary school if the child has received kindergarten education and the local area has enough educational resources to admit them.[23] Based on these facts and our DID estimates, it is plausible that the introduction of NCMS has led to less delay of schooling, either because NCMS relieves the financial burden of health care or because better access to health care makes more six-year-olds healthy enough for school. Unfortunately, we do not have individual level health utilization data distinguish these two explanations.

Table 12 reports the DID estimators according to whether a household has more or less percent of members being adult labor (age 17-60). In particular, we divide the households into four quartiles and obtain a separate set of parameters for each quartile. The DID estimators are mostly insignificant, except for 4 coefficients for households in the third quartile, 1 coefficient for the first quartile and 1 coefficient for the fourth quartile. This suggests that, even if the NCMS has improved the health of adult labor, increased their labor income, and made more financial resources available for child schooling, the effect is sparse and non-linear.

For other sub-groups (not reported), we find no more than 1 significant DID estimators by child gender, by whether a household has elderly members, by house value, and

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[22] See http://dailynews.sina.com/bg/chn/chnnews/chinanews/su/20100914/04411830677.html, accessed on September 14, 2010.

[23] See http://edu.ce.cn/young/campus/200912/07/t20091207_20566049.shtml, accessed on September 11, 2010.

by household head education. These results, combined with the above results by child age and adult labor, imply that the NCMS is not effective in improving the school enrollment of most vulnerable households, though there is some evidence that NCMS has reduced the delay of elementary education for six-year-olds.

6. Discussion and Conclusion

Overall, using a large cross-section from the 2006 China Agricultural Census, we find that NCMS-insured households on average have better outcomes in child school enrollment, young child mortality and pregnancy mortality than non-insured households. However, most of these differences are driven by the endogenous introduction and take up of the NCMS. Once we control for the selection bias in a difference-in-difference propensity score method, NCMS has close to zero effect on the average population, although there is moderate evidence that NCMS has reduced the delay of elementary education for some six-year-olds.

This finding of zero average treatment effect is consistent with the existing literature (Yi et al. 2009; Lei and Lin 2009), who attribute the lack of effect (on health care utilization and health improvement) to low reimbursement rate and selection. Wang et al. (2009) do find some positive effects of health insurance coverage on self-reported health status, but the insurance program they studied is different from NCMS and arguably more comprehensive in outpatient care and could offer more help to deal with non-catastrophic health risk.

Since our studied area is much poorer than most areas of China, we suspect the NCMS does not improve the three studied outcomes in other areas either. In addition to the low reimbursement rate as noted above, the lack of average effect may be explained by the facts that mortality is an extreme event and the effect of NCMS of school enrollment may take more than three years to show up in the data. Another possibility is that NCMS may encourage more health care utilization but the ease of financial burden has not appeared yet as households need to pay even more money out of pocket when they seek more treatment. Thanks to more government subsidy in 2009, reimbursement rate has increased over time. Whether this improvement implies better health and educational outcomes is a topic worth studying in the future.

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Figure 1: Histogram of village level take up rate, conditional on NCMS counties

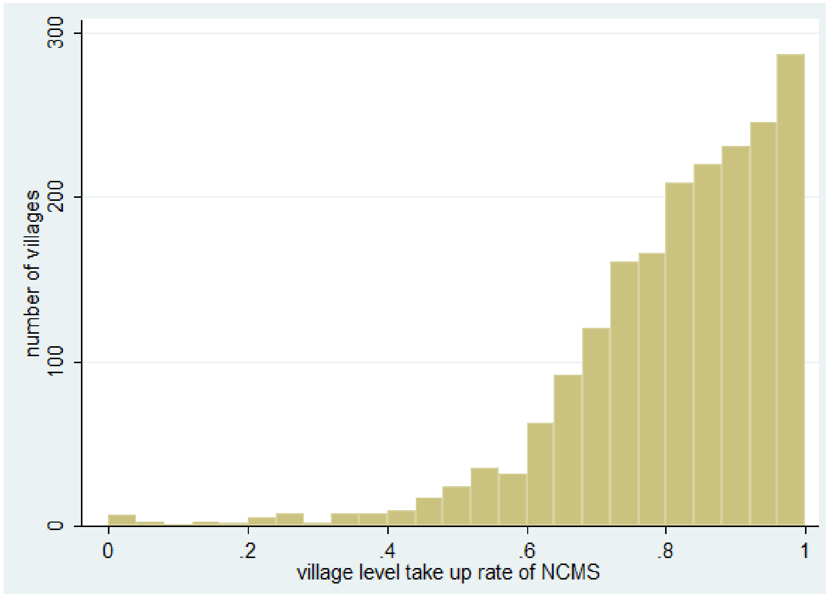


Figure 2: Propensity score distribution of NCMS and non-NCMS counties

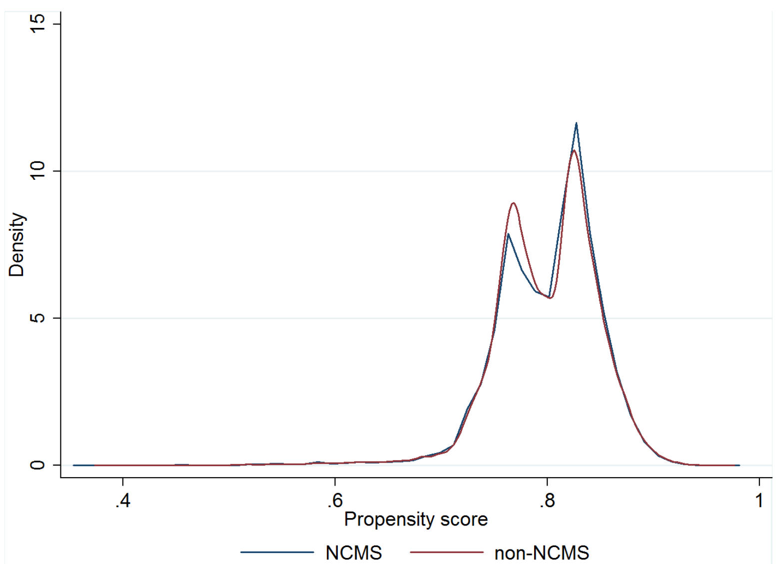
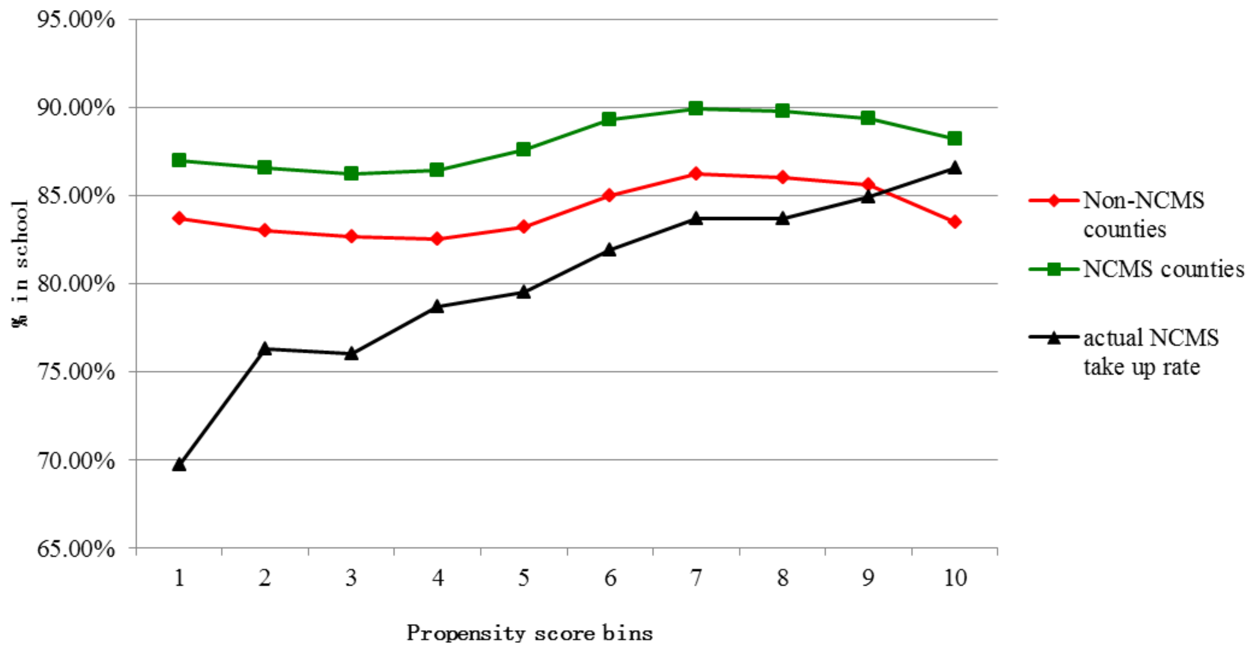


Figure 3: School enrollment rate by NCMS/non-NCMS counties and propensity score bins



Cutoff points for bin definition:

	Mean of p score	Min of p score	Max of p score
bin 1	0.71	0.355	0.745
bin 2	0.755	0.745	0.762
bin 3	0.768	0.762	0.774
bin 4	0.782	0.774	0.79
bin 5	0.798	0.79	0.806
bin 6	0.814	0.806	0.819
bin 7	0.824	0.819	0.828
bin 8	0.833	0.828	0.839
bin 9	0.846	0.839	0.855
bin 10	0.872	0.855	0.978

Table1: Summary of village-level mortality, by NCMS status

	non-NCMS counties	NCMS counties				
		All	County with NCMS in 2004	Counties with NCMS in 2006	village take up rate above median (83.8%)	village take up rate below median (83.8%)
Total # of villages	2017	1960	483	1477	980	980
# of young children mortality	1.10 (1.63)	0.77 (1.32)	0.69 (1.26)	0.86 (1.43)	0.755 (1.28)	0.787 (1.35)
0	52.65%	61.68%	67%	0.58%	61.3%	61.9%
1	18.69%	18.06%	17%	0.19%	19%	17.1%
2	13.09%	10.87%	0.09%	0.12%	11%	10.7%
3	8.28%	5.14%	0.04%	0.06%	5%	5.2%
3+	7.29%	4.25%	0.03%	0.05%	3.7%	5.1%
young children mortality rate	0.011 (0.016)	0.009 (0.018)	0.009 (0.01)	0.01 (0.024)	0.009 (0.02)	0.009 (0.04)
# of pregnant women mortality	0.059 (0.296)	0.028 (0.167)	0.021 (0.143)	0.03 (0.174)	0.026 (0.158)	0.029 (0.174)
0	95.14%	97.29%	97.9%	97.1%	97.43%	97.14%
1	4.31%	2.66%	20.1%	2.8%	2.57%	2.76%
2	0.25%	0.05%	0%	0.1%	0%	0.1%
2+	0.3%	0%	0%	0.05	0%	0%
pregnancy women mortality rate	0.023 (0.134)	0.011 (0.09)	0.012 (0.098)	0.01 (0.011)	0.008 (0.08)	0.013 (0.1)

Table 2: Summary of school enrollment, by NCMS status

	non-NCMS counties	NCMS counties					All counties	
		all	County with NCMS in 2004	Counties with NCMS in 2006	not enrolled in NCMS	enrolled in NCMS	male	female
Total # of school age children	776,854	643,831	151901	491930	128,166	515,665	763364	657334
% in school all age	84.13%	88.09%	86.5%	88.5%	86.27%	88.55%	85.4%	86.4%
age 6	29.28%	45.26%	36.7%	47.9%	41.19%	46.32%	37.5%	37.5%
age 7	79.97%	90.86%	86.3%	92.3%	88.94%	91.36%	85.8%	85.8%
age 8	91.74%	96.02%	94.4%	96.5%	94.79%	96.34%	94.2%	93.2%
age 9	95.14%	97.34%	96.4%	97.6%	96.55%	97.54%	96.4%	95.9%
age 10	95.58%	97.39%	96.8%	97.6%	96.53%	97.61%	96.7%	96%
age 11	96.52%	97.41%	97.2%	97.4%	96.79%	97.56%	97.1%	96.7%
age 12	95.79%	97.03%	96.5%	97.2%	95.98%	97.30%	96.6%	96%
age 13	95.14%	96.58%	95.5%	96.9%	95.65%	96.81%	96.1%	95.4%
age 14	91.49%	93.39%	92.3%	93.7%	91.22%	93.90%	92.9%	91.7%
age 15	85.13%	87.52%	86.6%	87.8%	84.91%	88.15%	86.9%	85.7%
age 16	68.86%	71.60%	73.9%	70.9%	68.10%	72.42%	70.9%	69.4%

Table 3: Across county comparison

County Name	A	B	C	D	E	F	G	H
Year to first adopt NCMS	2004	2006	2006	2006	2007	2007	2007	2007
Local fiscal income per capita (2004)[1]	162	166	122	320	141	149	114	68
Fiscal expenditure per capita (2004)[1]	493	381	352	660	499	434	366	398
Per capita income (2004)[1]	1562	1968	1503	2119	1540	1515	1511	1410
# of children per HH[2]	2.40	2.16	2.01	2.22	1.72	2.37	2.47	2.33
# of adult labor per HH[2]	2.42	2.49	2.39	2.42	2.34	2.41	2.41	2.52
fraction of HH with migrants[2]	0.05	0.25	0.25	0.28	0.34	0.19	0.16	0.33
Log(house value)[2]	9.44	9.70	9.55	9.67	9.79	9.64	9.44	9.65
contract land[2]	3.86	2.93	3.08	2.40	3.15.	2.35	3.37	2.84
fraction of HH with non-rural hukou[2]	0.02	0.02	0.03	0.02	0.05	0.02	0.03	0.03
fraction of HH with non-local hukou[2]	0.03	0.03	0.05	0.02	0.10	0.02	0.03	0.03
% of villages with national poverty status[2]	0.59	0.66	0. 37	0. 60	0.44	0.65	0.65	0.47
% of villages for minority gathering[2]	0.33	0.38	0. 35	0. 44	0.20	0.45	0.31	0.13

Note: 1. Source: the 2004 statistical year book of the study, in RMB. 2. Source: the study sample.

Table 4: Compare households across NCMS participants, NCMS non-participants and non-NCMS counties

	Non-NCMS	NCMS counties		
	counties	All	Non-takeup	Takeup
Household Variables				
years of edu of HH head	5.97	6.28	6.25	6.29
	(3.03)	(3.16)	(3.44)	(3.10)
household size	4.22	4.14	3.99	4.18
	(1.57)	(1.64)	(1.69)	(1.63)
# of 17-60 year old	2.46	2.5	2.37	2.54
	(1.28)	(1.43)	(1.41)	(1.44)
# of 60+ year old	0.38	0.42	0.4	0.43
	(0.69)	(0.71)	(0.70)	(0.72)
# of migrating workers	0.19	0.29	0.29	0.29
	(0.39)	(0.46)	(0.46)	(0.46)
have non-local hukou	0.04	0.04	0.05	0.03
	(0.19)	(0.19)	(0.24)	(0.19)
have non-rural hukou	0.037	0.04	0.08	0.03
	(0.19)	(0.20)	(0.27)	(0.18)
have government worker	0.02	0.02	0.04	0.02
	(0.14)	(0.14)	(0.20)	(0.12)
log (house value)	9.42	9.55	9.42	9.59
	(0.999)	(1.02)	(1.02)	(1.02)
contract land (mu)	3.35	2.97	2.7	3.03
	(2.55)	(2.33)	(2.27)	(2.35)
Village Variables				
is the center of the town	0.094	0.1	0.13	0.1
	(0.29)	(0.31)	(0.34)	(0.31)
is a minority gathering village	0.342	0.25	0.25	0.25
	(0.47)	(0.44)	(0.43)	(0.43)
has national poverty status	0.51	0.49	0.48	0.49
	(0.50)	(0.50)	(0.50)	(0.50)
distance to nearest elementary school (km)	1.47	1.2	1.2	1.2
	(2.12)	(1.96)	(1.87)	(1.97)
distance to nearest secondary school (km)	6.7	5.5	5.4	5.5
	(6.39)	(5.34)	(5.87)	(5.2)
distance to nearest hospital (km)	7.5	5.5	5.5	5.5
	(7.49)	(5.33)	(5.99)	(5.16)
Observation	726906	688328	136859	551469

Table 5: regression results of village-level mortality

	Any 0-5 year old death		Any pregnancy death	
NCMS offered	-0.087		-0.02	
	-1.49		-0.91	
NCMS take up rate	0.012	-0.031	0.003	-0.003
	0.17	-0.37	0.11	-0.12
is the center of the town	0.007	-0.005	0	-0.003
	-0.19	-0.16	0	-0.2
is a minority gathering village	-0.034	0.038	0.005	0.01
	(1.97)*	1.63	-0.76	-1.04
has national poverty status	0.023	0.004	-0.006	-0.008
	1.4	-0.19	-0.94	-1.22
# of households in the village	0	0	0	0
	(10.70)**	(6.72)**	(4.76)**	(4.03)**
distance to the nearest hospital	0.003	-0.001	0.002	0.001
	(2.32)*	-0.35	(2.35)*	-1.19
County dummies	No	Yes	No	Yes
Observations	3977	3977	3977	3977
R-squared	0.04	0.07	0.02	0.03

Errors clustered by township.
Robust t statistics in parentheses,* significant at 5%; ** significant at 1%

Table 6: OLS results of individual-level school enrollment

	(1) age 6-16	(2) age 7-15	(3) age 6-16	(4) age 7-15
NCMS offered	0.014	0.007		
	(4.93)**	(2.68)**		
NCMS takeup	0.018	0.014	0.017	0.013
	(8.36)**	(6.52)**	(8.64)**	(6.78)**
counties	All	All	All	All
town dummies	NO	NO	YES	YES
Observations	1420685	1154614	1420685	1154614
R-squared	0.28	0.05	0.29	0.06

All regressions control for individual, household and village variables as described in the paper. Error clustered by village. Robust t statistics in parentheses,* significant at 5%; ** significant at 1%,

Table 7: Classical propensity score matching, all using nearest neighbor matching

	Average treatment effect	std err	t-stat
Panel A: Conditional on 4 NCMS counties			
Individual level School Enrollment	0.016	0.001	11.38**
Panel B: Conditional on all 8 counties			
Individual level school enrollment	0.026	0.001	31.11**
Panel C: Conditional on all 8 Counties			
Village level of having any 0-5 year old death	-0.067	0.026	-2.63**
Village level young children mortality rate	0.000	0.001	0.154
Village level of having any pregnant women death	-0.013	0.009	-1.427
Village level pregnant women mortality rate	-0.003	0.003	-0.984

* significant at 5%; ** significant at 1%.

Table 8: DID estimates for village level mortality rate, including all 8 counties

Panel A: Predicted value of village medical insurance participation ratio

	Number	Mean	Std	Min	Max
Non-NCMS	2017	0.8	0.053	0.357	0.995
NCMS	1960	0.8	0.055	0.355	0.989

Panel B: DID estimates

	Children Death	Pregnant Women Death
bin 2 (lowest 20-40% of pscore)	-0.037	0.004
	-1.15	-0.25
bin 3	-0.057	-0.002
	-1.71	-0.11
bin 4	-0.033	-0.018
	-0.86	-1.08
bin 5 (highest 20% of pscore)	-0.065	-0.038
	-1.49	(-2.21)*
bin 2*NCMSoffered	-0.016	-0.012
	-0.31	-0.53
bin 3*NCMSoffered	-0.047	-0.027
	-0.95	-1.35
bin 4*NCMSoffered	-0.034	-0.004
	-0.66	-0.17
bin 5*NCMSoffered	-0.091	0.014
	-1.67	-0.66
NCMSoffered	absorbed	absorbed
county dummy	Yes	Yes
Observations	3977	3977
R-squared	0.06	0.02

Errors clustered by township. Robust t statistics in parentheses,* significant at 5%; ** significant at 1%.

Table 9: DID estimates for individual level school enrollment

	(1)	(2)
Sample	All counties	County A vs. non-NCMS counties
NCMS offered	-0.011	0.058
	(2.51)*	(9.49)**
bin 2 (lowest 10-20% of pscore)	-0.009	-0.015
	(3.06)**	(3.32)**
bin 3	-0.011	-0.02
	(3.25)**	(4.31)**
bin 4	-0.009	-0.014
	(2.65)**	(2.71)**
bin 5	0.000	-0.001
	(0.14)	(-0.34)
bin 6	0.011	0.008
	(3.26)**	(1.84)
bin 7	0.017	0.02
	(5.21)**	(4.25)**
bin 8	0.018	0.02
	(5.22)**	(4.01)**
bin 9	0.022	0.027
	(6.16)**	(4.98)**
bin 10 (highest 10% of pscore)	0.016	0.018
	(3.69)**	(3.08)**
bin 2 * NCMS offered	0.002	-0.006
	(0.600)	(-1.68)
bin 3 * NCMS offered	0.003	-0.002
	(0.69)	(2.46)*
bin 4 * NCMS offered	0.002	-0.004
	(0.51)	(-1.52)
bin 5 * NCMS offered	0.005	0.004
	(1.33)	(1.87)
bin 6 * NCMS offered	0.004	-0.005
	(1.09)	(-1.26)
bin 7 * NCMS offered	0.003	0.003
	(0.62)	(0.89)
bin 8 * NCMS offered	0.003	-0.001
	(0.75)	(0.71)
bin 9 * NCMS offered	0.003	0.002
	(0.62)	(0.40)
bin 10 * NCMS offered	0.006	-0.004
	(1.11)	(2.09)*
county dummies / individual variables	yes / yes	yes / yes
Observations	1420685	950681
R-squared	0.27	0.29

Error clustered by village. Robust t statistics in parentheses,* significant at 5%; ** significant at 1%.

Table 10: DID estimators, separating NCMSoffered and NCMStakeup

	School Enrollment
bin 2 * NCMS offered	-0.007
	(1.32)
bin 3 * NCMS offered	-0.009
	(1.23)
bin 4 * NCMS offered	-0.018
	(2.24)*
bin 5 * NCMS offered	-0.008
	(1.24)
bin 6 * NCMS offered	-0.007
	(1.23)
bin 7 * NCMS offered	-0.007
	(1.26)
bin 8 * NCMS offered	-0.003
	(0.56)
bin 9 * NCMS offered	-0.009
	(1.38)
bin 10 * NCMS offered	-0.011
	(1.63)
bin 2 * NCMS take up	0.012
	(2.45)*
bin 3 * NCMS take up	0.015
	(2.38)*
bin 4 * NCMS take up	0.025
	(3.48)**
bin 5 * NCMS take up	0.016
	(2.81)**
bin 6 * NCMS take up	0.013
	(2.63)**
bin 7 * NCMS take up	0.011
	(2.19)*
bin 8 * NCMS take up	0.007
	(1.37)
bin 9 * NCMS take up	0.012
	(2.29)*
bin 10 * NCMS take up	0.018
	(3.32)**
NCMStakeup	0.007
	(1.93)
NCMSoffered	absorbed
bin 2 – bin 10 dummies	Yes
County dummies / individual variables	Yes / Yes
Observations	1420685
R-squared	0.27

Error clustered by village. Robust t statistics in parentheses,* significant at 5%; ** significant at 1%.

Table 11: DID estimator on individual level school enrollment, by child age

	age 6	age 7	age 8	age 9-14	age 15-16
bin 2 * NCMS offered	0.002	0.022	0.003	-0.004	0.004
	(0.14)	(1.97)*	(0.51)	(1.1)	(0.36)
bin 3 * NCMS offered	0.009	0.009	-0.003	-0.001	0.006
	(0.59)	(0.75)	(0.38)	(0.18)	(0.51)
bin 4 * NCMS offered	0.004	0.012	0.006	0.002	0.000
	(0.23)	(0.97)	(0.76)	(0.42)	(0.03)
bin 5 * NCMS offered	0.028	0.021	0.002	0.002	0.001
	(1.87)	(1.71)	(0.27)	(0.60)	(0.08)
bin 6 * NCMS offered	0.029	0.005	0.000	-0.002	0.015
	(1.68)	(0.41)	(0.01)	(-0.49)	(1.44)
bin 7 * NCMS offered	0.038	0.007	0.007	-0.006	0.007
	(2.22)*	(0.59)	(0.97)	(-1.86)	(0.65)
bin 8 * NCMS offered	0.029	0.017	0.009	-0.002	0.006
	(1.68)	(1.34)	(1.29)	(-0.57)	(0.60)
bin 9 * NCMS offered	0.041	0.009	-0.006	-0.002	0.013
	(2.43)*	(0.70)	(0.82)	(0.70)	(1.18)
bin 10 * NCMS offered	0.038	0.006	0.004	-0.003	0.006
	(2.14)*	(0.44)	(0.42)	(0.75)	(0.50)
NCMS offered	absorbed	absorbed	absorbed	Absorbed	absorbed
bin 2 – bin 10 dummies	Yes	Yes	Yes	Yes	Yes
County dummies	Yes	Yes	Yes	Yes	Yes
Individual variables	Yes	Yes	Yes	Yes	Yes
Observations	192999	184504	191658	768766	236244
R-squared	0.11	0.07	0.03	0.02	0.05

Error clustered by village. Robust t statistics in parentheses,* significant at 5%; ** significant at 1%.

Table 12: DID estimator on individual level school enrollment, by % of household members being 17-60 year old (adult labor)

	% of adult labor 1st quartile	% of adult labor 2nd quartile	% of adult labor 3rd quartile	% of adult labor 4th quartile
bin 2 * NCMS offered	0.002	0.002	0.006	-0.001
	(0.28)	(0.42)	(1.15)	(-0.11)
bin 3 * NCMS offered	-0.006	0.007	0.015	0.001
	(-0.84)	(1.22)	(2.67)**	(0.12)
bin 4 * NCMS offered	-0.001	0.008	0.008	0.004
	(-0.16)	(1.24)	(1.35)	(0.56)
bin 5 * NCMS offered	-0.002	0.01	0.018	0.000
	(-0.39)	(1.70)	(3.19)**	(0.05)
bin 6 * NCMS offered	0.002	-0.003	0.009	0.015
	(0.34)	(-0.47)	(1.70)	(1.99)*
bin 7 * NCMS offered	-0.003	0.003	0.004	0.008
	(-0.43)	(0.57)	(0.70)	(1.04)
bin 8 * NCMS offered	0.001	0.004	0.012	-0.002
	(0.22)	(0.68)	(2.21)*	(-0.31)
bin 9 * NCMS offered	0.003	0.004	0.006	0.005
	(0.52)	(0.66)	(1.00)	(0.80)
bin 10 * NCMS offered	0.005	0.017	0.014	0.008
	(0.78)	(2.16)*	(2.29)*	(1.23)
NCMS offered	absorbed	absorbed	absorbed	absorbed
bin 2 – bin 10 dummies	Yes	Yes	Yes	Yes
County dummies	Yes	Yes	Yes	Yes
Individual variables	Yes	Yes	Yes	Yes
Observations	364480	380721	376187	299297
R-squared	0.32	0.33	0.28	0.18