Journal of Economic Behavior & Organization 97 (2014) 84–102

Contents lists available at ScienceDirect

Journal of Economic Behavior & Organization

journal homepage: www.elsevier.com/locate/jebo

Social learning and health insurance enrollment: Evidence from China's New Cooperative Medical Scheme☆

Hong Liu[a], Qi Sun[b,*], Zhong Zhao[c,d]

[a] China Economics and Management Academy, Central University of Finance and Economics, 39 South College Road, Beijing 100081, China
[b] School of International Business Administration, Shanghai University of Finance and Economics, 777 Guoding Road, Shanghai 200433, China
[c] School of Labor and Human Resources, Renmin University of China, 59 Zhongguancun Street, Beijing 100872, China
[d] Institute for the Study of Labor (IZA), Schaumburg-Lippe St. 5-9, 53113 Bonn, Germany

ARTICLE INFO

Article history:
Received 31 January 2013
Received in revised form 17 October 2013
Accepted 28 October 2013
Available online 7 November 2013

JEL classification:
I1
D83

Keywords:
Rural China
Health insurance
Social learning
Peer effects

ABSTRACT

This paper examines the role of social learning in household enrollment decisions for the New Cooperative Medical Scheme (NCMS) in rural China by estimating a static game with incomplete information. Using a rich dataset from the China Health and Nutrition Survey, we find that a 10-percentage-point increase in the enrollment rate in a village increases one's take-up probability by 5 percentage points. Using multiple model specifications, we show that the estimated social effects are not driven by simultaneity or common unobserved factors but are consistent with the hypothesis of social learning. We also find that the importance of social effects decreases significantly with households' familiarity with the NCMS as well as with the development of alternative information channels, which further ascertains that the primary mechanism for the social effects is social learning. The evidence suggests that healthier, wealthier, relatively well-educated, older Han male household heads tend to be opinion leaders.

1. Introduction

One of the main obstacles to social program take-up is a lack of information about the program (Moffitt, 1983; Craig, 1991; Currie, 2004). For instance, Aizer (2007) finds that information costs are an important contributor to the low take-up rate in the Medicaid program in the United States. This problem could be more serious in developing countries, as the official information transmission channels are typically inadequate. However, such informational barriers could be

☆ We would like to thank Alan Sorensen, Patrick Bajari, and seminar participants at Shanghai University of Finance and Economics, 2012 International Workshop on Research in Microeconometrics at Renmin University of China, and 2013 China Meeting of the Econometric Society for helpful discussions. We also thank William Neilson (Editor), an Associate Editor, and especially an anonymous referee for detailed comments and suggestions. We acknowledge the financial support from National Natural Science Foundation of China (Grant Nos. 71203244, 71303148, and 71173227), Humanity and Social Science Foundation of Ministry of Education of China (Grant No. 13YJC790126), Program for New Century Excellent Talents in University (Grant No. NCET-12-0993), and Shanghai Pujiang Program (Grant No. 12PJC053). This research uses data from the China Health and Nutrition Survey (CHNS). We thank the National Institute of Nutrition and Food Safety, China Center for Disease Control and Prevention; the Carolina Population Center, University of North Carolina at Chapel Hill, the National Institutes of Health (NIH; R01-HD30880, DK056350, and R01-HD38700), and the Fogarty International Center, NIH, for financial support for the CHNS data collection and analysis files since 1989. We thank those parties, the China-Japan Friendship Hospital, and the Ministry of Health for support for CHNS 2009 and future surveys.

* Corresponding author. Tel.: +86 21 65906917.
E-mail addresses: irisliu2000@gmail.com (H. Liu), sun.qi@mail.shufe.edu.cn (Q. Sun), mr.zhong.zhao@gmail.com (Z. Zhao).

0167-2681/$ – see front matter
http://dx.doi.org/10.1016/j.jebo.2013.10.012

reduced if information were transmitted through social learning, which refers to any mechanism through which people learn information from others before making decisions (Bandura, 1977). It may take the form of direct communication with or observation of others (Bikhchandani et al., 1998).

The main objective of this paper is to quantify the importance of social learning in household health insurance enrollment decisions by exploiting the unique opportunity of the recent establishment and expansion of the New Cooperative Medical Scheme (NCMS) in rural China since 2003, which is a voluntary public health insurance program for the rural population and is one of the pillars of China's social security system.

In the context of the NCMS, social learning may play a significant role in enrollment decisions and it is worth investigating for four reasons. First, as the NCMS is implemented in rural China, issues related to information barriers could be more serious because of the low education level of the rural population,[1] a poor official information sharing scheme and less transparent government policies.

Second, the operation of the insurance market in general is still new and complex for most households in rural China. Information on the procedures, payoffs and costs associated with the NCMS per se is limited because it is a newly established program. Although local government officials have exerted considerable efforts such as an intensive advertising campaign and door-to-door appeals (Wu et al., 2006; You and Kobayashi, 2009) to convey information to rural households, the details of the NCMS program are still difficult for rural households to understand. For example, Pan et al. (2009) find that approximately 78 percent of survey respondents were unfamiliar with the detailed NCMS regulations implemented in their counties.

Third, some studies find that when the NCMS was introduced, people had low levels of trust in local governments and were skeptical about the promised benefits of the NCMS, as the local governments had consistently imposed a number of taxes and fees on them but misused those funds in the past (Yip and Hsiao, 2009; Yi et al., 2011). This distrust, combined with the low education levels of the rural population and the complexity of the NCMS program, may substantially reduce the effectiveness of the official information campaign, and increase information barriers.

Finally, during the implementation phase of the NCMS, the social norms regarding and perceptions of the program were still being formed. Households in rural China typically live in close-knit villages, where they can effectively communicate with others. An individual villager can learn additional useful information from the behavior of his co-villagers, who might have better knowledge of or experience with health insurance, through word-of-mouth communication or observational learning. Therefore, social interactions and information exchanges among peers could have a long-term equilibrium effect on the take-up rate of the NCMS, which may be above or below than the optimal level (Dahl et al., 2012).

Relative to a growing body of literature studying different aspects of public insurance programs in China, such as design and implementation (Mao, 2005; Brown et al., 2009), and impact evaluation (Wang et al., 2009; Wagstaff et al., 2009; Lei and Lin, 2009), our study contributes to the literature by investigating the determinants of NCMS participation, with a particular focus on the role of social learning at the village level. Specifically, we aim to examine whether an individual's decision to enroll in the NCMS is affected by the decisions of his co-villagers due to the informational content embedded in such decisions, using data from the three most recent waves, 2004, 2006 and 2009, of the China Heath and Nutrition Survey (CHNS).

Our paper also contributes to the growing body of empirical literature on the effect of social learning in numerous contexts (Manski, 2000), such as health insurance plan decisions (Sorensen, 2006), retirement savings decisions (Duflo and Saez, 2002, 2003), welfare participation (Bertrand et al., 2000; Dahl et al., 2012), contraception decisions (Munshi and Myaux, 2006), and stock market participation (Hong et al., 2004). Our work is distinct from those listed above in the sense that during our 5-year data period, the NCMS passed through different stages, from inception to expansion and to full coverage, which allows us to investigate the social effects during different stages of the program.

Our empirical strategy also differs from the current practice in the literature. It is well known that the social effect is difficult to identify due to the mixture of simultaneous causality among peers, unobserved common factors within the peer group and endogenous selection into peer group (Manski, 1993, 2000). The existing literature generally adopts one of three approaches to overcome the identification problems. One is to use instrumental variables (e.g., Duflo and Saez, 2002; Chen et al., 2010) to account for the endogeneity of peers' decision. The second approach is to focus on a certain subsample and impose certain assumptions regarding the pattern of social learning to overcome the simultaneity problem. For example, Sorensen (2006) studies the social-learning effects on the employer-sponsored health plan choices of newly hired employees by assuming that their choices are influenced by the existing employees, but not vice versa. The third approach of studying the problem is to use a randomized experiment to generate exogenous changes in peer groups or exogenous variation in information exposure among peers (e.g., Duflo and Saez, 2003; Cai et al., 2009).

In this paper, we adopt a different approach to identify the effect of social learning using observational data. We model the NCMS participation process as a static game with incomplete information, in which households make NCMS enrollment decisions based on their own household-level characteristics (some of which are not observed by other households), village-level characteristics, and the enrollment decisions of other households in the same village. There are several reasons that this model is applicable to a social learning context. First, the benefits that a particular household can obtain from the NCMS crucially depend on the overall enrollment rate. Second, other households' enrollment decisions may reveal useful

[1] The overall education level of the Chinese rural population is quite low, with an average of 6.4 years of schooling based on the CHNS data.

information about an NCMS plan that a particular household does not have. Third, each household may possess some private information about their own benefits and costs associated with enrollment. Therefore, we assume that households in each village engage in an incomplete information game, and make enrollment decisions strategically.[2]

The structure and role of the village in rural China make the *village* a natural peer group (we will discuss this further in Section 2), which helps to avoid the issue of endogenous group membership. To account for the endogeneity of peer enrollment decisions due to simultaneity and time-invariant common unobservables, we follow Bajari et al. (2010) and apply a two-step approach with household-level fixed effects. This identification strategy requires appropriate exclusion restrictions that there exist covariates affecting the behavior of one particular villager but not other villagers. In our paper, we assume that the take-up decision of one household is influenced only by its own health conditions but not directly influenced by the health status of the co-villagers (we will discuss this identification condition in Section 3, and provide the justifications in Section 5). Our main finding is that a 10-percentage-point increase in the enrollment rate of other households in the same village increases one's own take-up probability by 5 percentage points.

Taking advantage of the panel nature and the richness of the dataset, we conduct two robustness checks to show that the estimated peer effects are not driven by time-variant common unobserved factors at the village or county level, but are fully consistent with the hypothesis of social learning. It is found that the peer effects increase with spatial proximity among household heads. The pattern within subgroups of the villagers is that healthier, wealthier, relatively well-educated, and older Han male household heads tend to be opinion leaders in the village.

Moreover, we use different model specifications to further ascertain that the most likely mechanism for the estimated social effect in NCMS enrollment decisions is information transmission via social learning, but not other plausible alternatives, e.g., the desire to conform to peers' actions. We find that the importance of social effects decreases significantly with households' familiarity with the NCMS as well as with the development of alternative information channels. These findings have important policy implications, since they suggest that low income families and families living in relatively poor villages are influenced by social effects to a greater extent.

The remainder of the paper is organized as follows. Section 2 briefly describes the institutional background of the NCMS in China. Section 3 outlines our econometric model and the estimation strategy. Section 4 describes the data and main variables. Section 5 presents our empirical findings, and Section 6 discusses the policy implications of our results. Section 7 concludes.

2. Background

Prior to the economic reforms of the late 1970s, a village-based rural health insurance system, known as the Cooperative Medical Scheme (CMS), covered 90 percent of Chinese rural residents and was their primary channel for accessing basic health services (Feng et al., 1995; Liu, 2004b; You and Kobayashi, 2009). Along with the transition from the collective commune system to the "household responsibility system" beginning in 1978, the CMS collapsed in most rural areas because it lost its main financial support from the collective commune welfare fund. The health insurance coverage rate dropped dramatically from 90 percent in 1980 to 5 percent in 1985 (Liu and Cao, 1992). Since then, most rural residents have remained uninsured. According to the China National Health Service Survey, over 87 percent of the 0.9 billion rural residents did not have any health insurance in 1998 (Liu, 2004a), and the uninsured rate was still nearly 80 percent in 2003.

To improve health care access for rural residents, the Chinese government began to implement a nationwide project known as the New Cooperative Medical Scheme (NCMS) in rural China in 2003. It was first implemented in 304 pilot rural counties, was expanded to 1451 counties (approximately 50 percent of all rural counties) in 2006, and to nearly all rural counties (approximately 95 percent) by 2008. This program covered 835.6 million rural residents, nearly two-thirds of the Chinese population in 2010.

According to the broad guidelines issued by the central government, the NCMS is a voluntary public insurance program operated at the county level. The NCMS seeks to provide low-cost basic health care services, including inpatient, catastrophic, and some types of outpatient care, for the entire rural population. To reduce the adverse selection associated with the voluntary nature of the NCMS, participation in the NCMS is required at the household level.[3]

The details of the NCMS are complicated and vary across counties. For example, the funding for the NCMS comes from three main sources, including subsidies from the central government, local (mainly provincial) government, and individual contributions. The shares of contributions from different sources differ and change over time. In 2003, the minimum per capita premium included a 10 RMB[4] contribution from the individual, a subsidy of 10–20 RMB from the local government, and a 10 RMB subsidy from the central government for the enrollees in the poorer central and western regions. The subsidies per person from both the central and local governments were raised to 40 RMB in 2006 and then 80 RMB in 2008. The minimum individual contribution was also raised from 10 to 20 RMB per person. In 2009, the average premium was 113 RMB per person, and the subsidies from central and local governments account for about 71 percent of the total premium (Fig. 1).

[2] If rural households have a desire to conform to the behaviors of their co-villagers, it could be another channel for peer effects. We will test the social-learning hypothesis against this channel using different model specifications in the paper.

[3] Despite this requirement, some local governments also allow for enrollment at the individual level in practice to achieve high levels of enrollment.

[4] From 2003 to 2007, 1 USD ≈ 8 RMB; from 2007 to 2010, 1 USD ≈ 7 RMB.

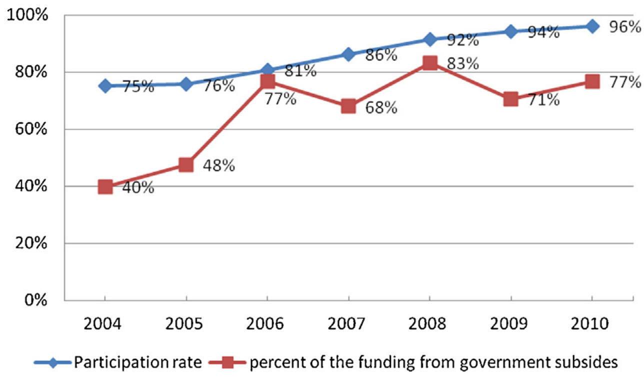

Fig. 1. NCMS participation rate and government subsidies in rural China.
Data source: China Health Statistics Yearbook 2009–2011.

Table 1
Village-level enrollment rate in counties with NCMS newly introduced.

Wave	Num. of counties	Num. of villages	Mean	Std. Dev.	Min	Max
2004	6	15	0.550	0.392	0	1
2006	23	62	0.741	0.246	0	1
2009	19	51	0.886	0.198	0	1
Estimated S.D. of county effect				0.193		
Estimated S.D. within counties				0.190		

The NCMS plans in all counties cover inpatient care, but differ in their coverage for outpatient services. Approximately 72 percent of the counties cover outpatient services through a household account or on a pooled basis. Among the rest, approximately 11 percent of the counties cover only outpatient services for catastrophic diseases, and approximately 17 percent do not cover outpatient services at all (Lei and Lin, 2009; You and Kobayashi, 2009; Wagstaff et al., 2009). The enrollees can only visit certain approved facilities to be eligible for reimbursement, and can be reimbursed immediately or later on at a health facility or other agency, depending on local policies. The reimbursement rates, deductibles and ceilings also vary across facility types. These complicated regulations inevitably generate considerable information costs and barriers for rural households.

Fig. 1 shows the NCMS participation rate and the percentage of financing from government subsidies in rural China from 2004 to 2010, based on official national statistics. Surprisingly, the take-up rate of the NCMS was approximately 75 percent during the initial stage in 2004, increased steadily to 81 percent in 2006, and reached 96 percent in 2010. Compared to many voluntary social programs in other countries, such as the Medicaid program in the United States, the high take-up rate of the NCMS is an achievement in itself.[5]

Such high levels of participation may be the result of the relatively generous government subsidies for the NCMS and the household-based enrollment requirement (Wagstaff et al., 2009). However, as shown in Table 1, the village-level enrollment rates varied considerably, ranging from zero enrollment to full enrollment within the NCMS counties when the NCMS was newly introduced in each wave.[6] The estimated standard deviation within counties is approximately 0.19, similar to the estimated standard deviation across counties, which cannot be explained by common NCMS policies at the county level. Therefore, it is important to understand the mechanism underlying the NCMS take-up decision and investigate what explains the high overall take-up rate and different take-up rates at the village level, which may have important implications for other social programs in China and in other countries in general.

Given the experiences of other developing and developed countries, a lack of information is an important barrier to participation in social programs (Moffitt, 1983; Currie, 2004), as learning about a program, its eligibility requirements and how to apply is costly and time-consuming (Kleven and Kopczuk, 2011). In this paper, we consider the possibility that NCMS participation is influenced by social learning, which have been shown to be an important information transmission channel for individual decisions on program participation (Bertrand et al., 2000; Duflo and Saez, 2002; Munshi and Myaux, 2006; Sorensen, 2006; Dahl et al., 2012).

Following the empirical literature on social learning in the context of rural societies (Foster and Rosenzweig, 1995; Munshi, 2004), we define rural villages as peer groups, as each village in China is a closely-knit, long established social group (Chen et al., 2010; Brown et al., 2011). A typical village in China consists of 50–100 families and approximately 500 individuals, who belong to perhaps 7–10 clans. Most villagers live within walking distance of one another, and usually know

[5] According to the studies summarized in Sommers et al. (2012), the estimated adult take-up rates in Medicaid range from 32.3 percent to 81.3 percent.
[6] In our sample, each wave has a village with zero enrollment and a village with full enrollment.

each other well, due to the low population mobility resulting from the restrictions imposed by the household registration system (*Hukou*) and close local ties spanning generations. Mangyo and Park (2011) also show that geographic reference groups are more salient for rural residents than urban residents in China. Therefore, presumably, rural residents in the same village may learn much of the information on application procedures, reimbursement hassles, choice and the quality of the facilities, trust-worthiness of the NCMS, etc., from each other through formal or casual/word-of-mouth communications or by observational learning.

3. Econometric specification

Empirically, we first aim at identifying and estimating the endogenous peer effects (Manski, 1993), e.g. the causal effects of peer group's actions on the action of an individual member.[7] Furthermore, we investigate the mechanisms underlying the effects and examine whether social learning is the main channel. To achieve this, we model the NCMS participation process as a static game with incomplete information among households in a village, in which one household's enrollment decision depends on other households' decisions as well as its own and village-level characteristics. As Manski (1993) states, there are three endogeneity issues that may bias the estimation: simultaneous causality, common unobservables (time-invariant and time-variant), and endogenous selection into peer groups.

In our empirical analysis, the issue of selection into peer groups is not a concern, as villages are naturally occurring peer groups as described in Section 2. Due to the restrictions of the *Hukou* system, it is impossible for rural residents to move to other villages to obtain NCMS benefits, and migration into or out of a village is very low.

Simultaneity is one of the main difficulties inherent in estimating the causal social effects, as the households in the same village tend to co-influence each other. It may lead to an over-estimation of the importance of social effects in NCMS enrollment decisions.

We also need to separate the social effect from the impact of common unobservables in this analysis. For example, as another channel of information transmission, an unobserved local official information campaign may cause rural households in a village to make similar enrollment decisions. The positive correlation between an individual's decision and co-villagers' decisions could simply reflect unobserved, county- or village-specific common NCMS policies, shared characteristics of health resources, correlated preferences, etc., instead of informational spillovers.

Therefore, to address the problems of simultaneity and common unobservables, we employ a two-step estimation method that was pioneered first in estimating dynamic discrete games. In the following, we specify the econometric model, present the estimation methods, and discuss identification conditions in details.

3.1. Model

In rural China, households from the same village are eligible for the same NCMS plan and the enrollment is at the household level in the sense that each household can choose to have either all or none of its household members participate. We index a village by g where a particular NCMS plan is implemented, and a household that is eligible for the NCMS by i. Let y_{igt} be the NCMS participation decision of household i, where $y_{igt}=1$ indicates that household i in village g has chosen to participate in the NCMS in period t and $y_{igt}=0$ otherwise. The enrollment decision of household i, y_{igt}, is determined by the following equation:

$$y_{igt} = x_{igt}\beta + \delta\left(\frac{1}{N_g - 1}\right)\sum_{j\neq i} y_{igt} + z_{gt}\eta + c_i + \varepsilon_{igt} \tag{1}$$

The enrollment decisions of other households in the same village are summarized in the term $(1/(N_g-1))\sum_{j\neq i} y_{igt}$, which is the proportion of households other than i from the same village that choose to participate in the NCMS in period t. The coefficient δ measures the direction and the magnitude of the village-level peer effect. The vector x_{igt} contains observed household characteristics, while c_i represents an unobserved household or village characteristic that is fixed across t. The vector z_{gt} contains observed village-level characteristics. Finally, ε_{igt} is a stochastic preference shock, which is household i's private information. We assume that ε_{igt} is *i.i.d.* across i, g, and t.

3.2. Estimation

Eq. (1) essentially describes a discrete game in which a household's NCMS enrollment depends on the enrollment decisions of other households in the same village. It can be regarded as a special case of dynamic discrete games with zero discount

[7] As documented in the literature, there may be another type of peer effects, called exogenous peer effects or contextual effects (Manski, 1993, 2000), in which one's action varies with exogenous characteristics of the peer groups. We follow the relevant literatures on social learning in the context of program participation decisions (Duflo and Saez, 2002; Sorensen, 2006; Dahl et al., 2012), and assume that the exogenous characteristics (e.g. age or gender) of co-villagers cannot directly affect an individual household's insurance take-up behavior, but allow for an indirect effect through co-villagers' take-up behaviors.

factor in the empirical industrial organization literature. An important insight in the recent literature on such discrete games is that it is often easier and more straightforward to estimate it in two steps (e.g. Aguirregabiria and Mira, 2007; Bajari et al., 2007; Pakes et al., 2007; Bajari et al., 2010).[8] In general, these two-step methods suggest that, in the first step, the econometrician estimates the conditional probability that one of a finite number of possible outcomes is observed. Then, in the second step, the econometrician estimates the full model using the estimated probabilities from the first step as the controls. Such two-step approach applies to the cases where the first stage regressors are discrete or continuous, and the first-stage estimation does not need to be correctly specified (White, 1982; Aguirregabiria and Mira, 2007; Bajari et al., 2010).

In this paper, we apply a simple and flexible two-step method proposed in Bajari et al. (2010). In the first step, we estimate each household's NCMS enrollment probability y_{igt} on third-order splines of household-level characteristics, a household fixed effect, and a set of year dummies. The third-order spline is used to allow for more flexible first stage estimation compared to a linear regression of y_{igt} on household characteristics, household fixed effect, and year dummies. Then, we calculate the fitted value $\hat{y}_{igt}$, from the first stage regression and replace the term $(1/(N_g-1))\sum_{j\neq i}y_{igt}$ by $(1/(N_g-1))\sum_{j\neq i}\hat{y}_{igt}$. In the second stage, we proceed to estimate Eq. (1) with estimated peer enrollment using the standard linear panel data method, and obtain the consistent estimates of β, δ, and η.

As Bajari et al. (2010) suggest the estimator we use in this paper belongs to the class of semiparametric estimators considered in Newey (1994). One of the properties of such estimators is that the second-stage parameter estimator converges at a rate of $\sqrt{N}$, regardless of the convergence rate in the first stage. In addition, the asymptotic variance in the second stage is independent of the estimation method used in the first stage. Therefore, these properties allow us to use bootstrap to calculate the standard errors of the second-stage estimates.

In addition, such two-step methods are flexible enough to control for the common unobservables under certain assumptions. For example, if we assume that the common unobservable is an unknown but smooth function of the observed variables as in Bajari et al. (2010), we can control for the common unobservable in the second stage estimation by either using a fixed-effects model (e.g. Bajari et al., 2010), or applying the Mundlak representation (Mundlak, 1978; Li et al., 2013).

3.3. Identification

To handle the simultaneity problem inherent in our model, we need appropriate exclusion conditions to achieve identification in the two-step estimation (Matzkin, 1992; Bajari et al., 2010). In general, we need covariates that directly influence the NCMS enrollment decision of a particular household but do not directly influence other households. In this study, these covariates include variables that indicate the health condition of the household, i.e., an indicator of whether the household head has any chronic disease and the number of household members with chronic diseases. This assumption implies that the NCMS enrollment decision of household i is only directly determined by the health status of its own members but is not directly affected by the health status of other households $-i$ in the same village. Therefore, if the health status of other households $-i$ are excluded from the explanatory variables for household i's enrollment decision in both stages of estimation, this simultaneity problem can be solved.

There are several reasons for the validity of our exclusion conditions. First, we only assume no direct effects of peers' health status on one's insurance take-up decision, but allow for the situation in which health status of other households $-i$ affects household i's decision indirectly through peers' take-up decisions. For example, when observing peers' worsening health conditions, one's insurance take-up decision may vary with the insurance status of the peers, as the insured and uninsured peers would have different out-of-pocket medical expenses even for the same health problem. Second, this assumption follows most health economics literatures in which one's own health status, but not peers' health status, serves as the key determinant in one's demand for health insurance (e.g. Cameron et al., 1988; Krueger and Kuziemko, 2013). In the relevant literature on social learning, for example, Sorensen (2006) makes a similar and perhaps more plausible assumption that the existing employees' exogenous characteristics (including health status) have no direct effects on new hires' health plan choice. Nevertheless, such assumption should not be taken for granted and need to be discussed and tested in the context of each individual study. We have to assess the plausibility of this assumption in our context, i.e., to gauge the possibility that co-villagers' health status may directly affect one's health insurance demand independent of their insurance status.[9] We conduct several empirical tests to show the validity of our exclusion conditions, which will be discussed in detail in Sections 5.1 and 5.2.

With the above exclusion condition, our first stage now becomes regressing the NCMS enrollment y_{igt} on the indicator whether the household head has any chronic disease, a third-order spline of number of household members with chronic diseases, a household fixed effect, and a set of year dummies.[10]

[8] Instead of computing the equilibrium through the computationally intensive fixed point algorithm (e.g. Rust, 1987; Aguirregabiria and Mira, 2002), such two-step method estimates the equilibrium using the observed outcomes.

[9] As the referee has pointed out, in some cases it may be possible that peers' health status could directly affect one's health insurance demand by changing his/her subjective perception of the distribution of his own medical expenditure, independent of peers' insurance status. However, the empirical tests of the validity of our exclusion conditions help us to show such effect is not significant in our setting.

[10] We also experiment with different specifications in the first stage. As reported in Table A1, the results show that the estimated peer effects are robust across different first stage specifications, which is consistent with the literature (White, 1982; Aguirregabiria and Mira, 2007; Bajari et al., 2010).

In the second stage estimation, we deal with the problem of observed or time-invariant unobserved common factors in several ways. First, in addition to household-level characteristics, we control for a rich set of village-specific factors that may be correlated with the NCMS enrollment decisions of households in the same village. We also include a full set of province and wave dummies to control for regional differences and common time trends that could not be attributed to any of the explanatory variables in the model. Second, we control for time-invariant unobserved heterogeneity at the county (program), village and household levels using fixed effects specifications.

In addition, we also perform two robustness checks to investigate the possible importance of time-variant unobservable effects in our model. We look at various subgroups within a county or a village, and examine the peer effects within subgroups as well as across subgroups. The basic idea is that, if the correlation of NCMS enrollment decisions is driven by the time-variant common unobservables at the village or county level, we should observe both significant within-subgroup *and* significant cross-subgroup effects in peer enrollments. In contrast, if there only exist significant within-group *or* significant cross-group effects, it should enable us to rule out the possibility that time-variant unobserved common factors at the village or county level are the main driving force of the peer effects in our context (see Section 5.2).

4. Data and variables

4.1. Data

Our data come from the China Health and Nutrition Survey (CHNS), conducted by the Carolina Population Center at the University of North Carolina Chapel Hill and the National Institute of Nutrition and Food Safety of the Chinese Center for Disease Control and Prevention. The CHNS is an ongoing longitudinal survey with eight waves of data in 1989, 1991, 1993, 1997, 2000, 2004, 2006, and 2009. It contains rich information on individual, household and village (or community in urban areas and suburbs) characteristics, allowing researchers to study social and economic changes in China and their effects on the economic, demographic, health and nutritional status of the population.

The CHNS data cover 9 out of 31 Chinese provinces, including Guangxi, Guizhou, Heilongjiang, Henan, Hubei, Hunan, Jiangsu, Liaoning, and Shandong, which differ considerably in geography, economic development, public resources, and public health conditions. These sample provinces host approximately 45 percent of China's total population. The CHNS uses a multistage, random cluster-sampling approach to construct the sample. In each sample province, counties were initially stratified into low, middle, and high income groups, and four counties were then randomly selected based on a weighted sampling scheme. The provincial capital and a low-income city are selected when feasible. Villages and townships were selected randomly within the counties, and urban and suburban neighborhoods within the cities. In 2004–2009, there were approximately 218 primary sampling units, consisting of 36 urban neighborhoods, 37 suburban neighborhoods, 37 town neighborhoods[11] and 108 rural villages, which are all entities legally identified by the National Bureau of Statistics of China, referred to as "communities" in the CHNS. In this paper, as we only use the rural sample, we use "communities" and "villages" interchangeably.

In this study, we use the last three waves of CHNS data (2004, 2006, 2009) and focus on rural residents in rural areas,[12] including approximately 3000 households each wave. For the purposes of this study, our sample is further restricted to households living in counties where the NCMS has been introduced. Although the CHNS has no survey questions directly related to the NCMS status at the county level, the confidential community surveys collected information from the community head or community health workers and asked whether there was a Cooperative Medical Scheme in this community and if so for how long. As the NCMS was implemented in rural areas beginning in 2003, those villages where it was implemented in 2003 or later are considered NCMS villages. According to the government guideline that the NCMS should be managed at the county level, we classify a county with any village implementing the NCMS program as a NCMS county. Furthermore, based on the same survey questions, we can also determine when the NCMS was introduced in the county, that is, before 2004, between the 2004 and 2006 waves, or between the 2006 and 2009 waves.

In addition, we exclude approximately 9 percent of sample observations with missing values for health facility information at the community level and approximately 1 percent of sample households missing data on important demographic or socio-economic characteristics. The final study sample consists of 3,266 households, including 233 in 2004, 866 in 2006, and 2,167 in 2009.

4.2. Variables

The dependent variable is a dichotomous measure indicating household participation in NCMS. In the 2004 and 2006 waves, the CHNS asked each respondent whether he/she had cooperative medical insurance, but made no distinction between old and new schemes. In the 2009 wave, respondents were asked specifically about enrollment status in the NCMS. As the study sample is restricted to counties where the NCMS has been implemented, it is reasonable to consider

[11] CHNS 2004 has only 35 town neighborhoods.

[12] According to the administrative definition in China, city neighborhoods and county towns are regarded as urban areas, while suburban and rural villages are treated as rural areas.

Table 2
Summary statistics.

Variable	Full sample		Wave 2004	Wave 2006	Wave 2009
	Mean	Std. Dev.	Mean	Mean	Mean
Dependent variable					
Household enrollment status	0.853	0.354	0.579	0.737	0.929
Explanatory variables					
Household head's characteristics					
Age	54.177	12.578	52.938	52.271	55.072
Chronic disease	0.117	0.321	0.077	0.077	0.137
Female	0.153	0.360	0.193	0.140	0.154
Married	0.847	0.360	0.850	0.873	0.836
Han	0.812	0.391	0.854	0.773	0.823
Education: primary school	0.291	0.454	0.296	0.291	0.290
Education: junior high school and above	0.433	0.496	0.485	0.445	0.422
Other household characteristics					
Household size	3.532	1.596	3.279	3.482	3.579
Total household income (k)	27.012	36.583	15.089	21.064	30.670
Number of children under age 18	0.667	0.831	0.494	0.687	0.678
Number of elderly members	0.722	0.974	1.253	0.530	0.741
Number of members with chronic diseases	0.226	0.475	0.159	0.164	0.257
Village characteristics					
Any health facility in the village	0.889	0.314	0.966	0.828	0.905
Physician density	0.014	0.177	0.000	0.046	0.003
Village had health insurance in 2000	0.382	0.486	0.335	0.441	0.364
Prevalence of chronic diseases	0.074	0.055	0.052	0.054	0.084
Village urbanicity index	51.959	13.107	50.796	47.394	53.909
Population density score	5.257	1.364	4.796	5.219	5.321
Communication score	5.765	1.424	5.016	5.431	6.028
Access to convenient internet service	0.488	0.500	0.365	0.313	0.597
Access to convenient cell phone service	0.807	0.395	0.845	0.697	0.863
Number of household observations	3266		233	866	2167
Number of villages			15	75	129
Number of NCMS cities/counties			6	28	48

Note: In each wave of CHNS 2004–2009, there are 54 sample cities or counties.

the CMS enrollees in the NCMS counties as NCMS participants in the 2004 and 2006 waves. We use the household head's participation status as the primary measure of household enrollment. It is coded 1 if the household head is enrolled in NCMS and 0 otherwise. Using this measure, we find that 58 percent of the households in 2004, 74 percent in 2006, and 93 percent in 2009 selected to participate in the NCMS.[13]

Table 2 presents the summary statistics of key variables for household head, household and village. Household head variables include age,[14] gender, ethnicity (Han and ethnic minorities),[15] marital status, the presence of chronic disease (hypertension, diabetes, heart disease, stroke, and asthma), and education level (illiterate, primary school, junior high school and above). Household-level variables include household size, total household income (in 2009 Chinese RMB), the number of children under age 18, the number of elderly family members over 60, and the number of family members with chronic diseases.

Village-level variables include a binary variable indicating the presence of a health facility; physician density, calculated as the number of doctors in the village divided by the village population size; a binary indicator whether the village had any health insurance in 2000, which measures the health insurance history of the village and reflects people's knowledge about health insurance prior to the introduction of NCMS; the prevalence of major chronic diseases (hypertension, diabetes, heart disease, stroke, and asthma); village population density, and the urbanicity index. The urbanicity index is developed by Jones-Smith and Popkin (2010) to measure the levels of development and urbanization for each rural village and urban community in the CHNS data, based on 12 components.[16] Due to a lot of missing information on the areas of villages, we

[13] These coverage rates based on our sample are slightly lower than national statistics. It may be because our sample size is much smaller, especially in wave 2004. And our calculations are at household level, whilst national statistics are based on individual data.
[14] The age range of household heads is from 21 to 94.
[15] In China, the Han Chinese is the largest ethnic group and account for about 90 percent of the rural population, according to the 2000 population census of China.
[16] The 12 components of the urbanicity index include population density, economic activity, traditional market, modern market, transportation infrastructure, sanitation, communications, housing, education, diversity, health infrastructure, and social services.

cannot directly calculate population density for each village. It is measured by the scaled score of village population density,[17] which is one of the 12 components of the urbanicity index ranging from 0 to 10. There are three variables measuring the development of modern information technology in each village, including overall communication scores, which is another component of the urbanicity index,[18] and two indicator variables whether there are convenient internet service or cell phone service available in the village.[19]

5. Results

5.1. Baseline effect of social learning on NCMS enrollment

Table 3 presents our baseline results from the second stage using the two-step approach.[20] We have two specifications for the second stage estimation: random effects (RE) and fixed effects (FE) models. Standard errors are computed by bootstrapping over the two steps with 500 replications. For comparison, we also conduct RE and FE estimations without peer effects (columns (1) and (2)) and using the simple average enrollment in the village to replace the estimates from the first-stage as the key independent variable (columns (3) and (4)).

In columns (3) and (4), we find that the co-villagers' enrollment decisions have had a significant effect on an individual household's take-up probability. However, the estimated coefficients (0.73–0.74) based on the reduced form regressions tend to overestimate the actual magnitude of social effects because they fail to address the endogeneity problem caused by simultaneous causality and correlated unobservables (Manski, 1993). After eliminating the endogeneity bias using the two-step approach in columns (5) and (6), we still find a significant positive social effect, but the estimates are much smaller, approximately two-thirds the size of the reduced form estimates. Both the RE and FE estimates show statistical significance at the 1 percent level. The FE estimate is smaller than the RE estimate, but the magnitude, 0.498, is still economically large, suggesting that a 10-percentage-point increase in the enrollment rate of other households in the same village increases a household's take-up probability by 5 percentage points.

To place the importance of this social effect into perspective, we can compare our main estimate in column (6) to the impact of price on health insurance demand. The literature indicates that the price elasticity of demand for non-group health insurance in the US ranges from −0.3 to −0.87 (Gruber and Poterba, 1994; Marquis and Long, 1995; Congressional Budget Office, 2005; Krueger and Kuziemko, 2013). Therefore, 10-percentage-point increase in the proportion of peer enrollment in this study has the same influence on individual enrollment probability as 6–16 percent decrease in insurance premiums in the US individual health insurance market. Unfortunately, we cannot obtain price elasticity estimates for the NCMS because of the lack of data on premiums, and few studies estimate the price elasticity of health insurance demand in China.

Another way to understand the magnitudes of estimated social effects is to compare them to peer effects in other contexts. The study most similar to ours is Sorensen (2006), which examines individuals' choices of employer-sponsored health plans in California. He finds that the estimates for social effects are approximately 1.4–2.1, three to four times ours. However, in contrast to our study, Sorensen (2006) estimates discrete choice models, and his estimates suggest that 10-percentage-point increase in the share of a particular health plan in the department increases the probability that an employee will select this plan by 14–21 percentage points. In another study in the Chinese context, Chen et al. (2010) find that if the migration rate of the co-villagers increases by 10 percentage points, this will increase an individual's migration probability by 7.27 percentage points in rural China, which is slightly larger than our estimate.

As discussed in Section 3.3, our identification depends on the validity of our exclusion condition that peers' health conditions do not *directly* affect one's NCMS enrollment decision. We assess whether our exclusion conditions are valid in three ways. First, we add the village-level prevalence of chronic disease, calculated based on our CHNS sample, in the second stage estimation. The results in columns (7) and (8) of Table 3 show that the estimated coefficient on this variable is −0.019 for the RE specification and 0.462 for the FE specification, but both are statistically insignificant,[21] suggesting that co-villagers' health conditions pass the exclusion restriction.

The second way to assess the plausibility of our identification assumption in the two-step procedure is to replace the outcome of NCMS take-up decision with rural resident's age in our estimations. This is the test suggested in Duflo and Saez (2002). The intuition behind this test is that rural residents' age may be correlated within the village due to similar

[17] Jones-Smith and Popkin (2010) calculate the population density based on total population and total area of each rural and urban community from official records, but only release the scaled score in the CHNS. We cannot conduct such calculations because of no access to geographic codes.

[18] Based on CHNS data, Jones-Smith and Popkin (2012) use 7 variables to characterize the communication system in each community, including the availability (within community boundaries) of a cinema, newspaper, postal service, and telephone service and percent of households with a computer, the percent of households with a television, and the percent of households with a cell phone.

[19] Table 2 shows the summary statistics of counties with the NCMS program. Therefore, some of the statistics may not be consistent with the trend at the national level or the trend calculated from the whole CHNS sample. For example, it shows in Table 2 that the access to cell phone services decreased in 2006 in our sample; but based on the whole CHNS sample, access to convenient cell phone service improved over time from the mean 0.76 in 2004 to mean 0.78 in 2006 and then 0.85 in 2009.

[20] The results for the first stage estimation are reported in Table A1.

[21] We also find that the prevalence of chronic diseases in the village is insignificant in the estimations without control for peer effect, although unreported here.

Table 3
Social effects of NCMS.

	No peer effect		Use simple average		Two-step estimation		Two-step estimation	
	RE (1)	FE (2)	RE (3)	FE (4)	RE (5)	FE (6)	RE (7)	FE (8)
Peer enrollment in the village			0.742***	0.732***	0.613***	0.498***	0.613***	0.501***
			(0.034)	(0.069)	(0.063)	(0.139)	(0.070)	(0.144)
Prevalence of chronic diseases in the village							−0.019	0.462
							(0.313)	(1.012)
Age	0.004	−0.009	0.004	−0.009	0.003	0.002	0.003	0.002
	(0.004)	(0.108)	(0.003)	(0.101)	(0.004)	(0.289)	(0.004)	(0.363)
Age squared	−0.000	0.001***	−0.000	0.001***	−0.000	0.001*	−0.000	0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Chronic disease	0.006	0.003	0.010	−0.005	0.017	0.009	0.017	0.009
	(0.028)	(0.070)	(0.026)	(0.065)	(0.029)	(0.104)	(0.034)	(0.098)
Female	0.008	.	0.009	.	0.008	.	0.008	.
	(0.020)	.	(0.019)	.	(0.020)	.	(0.022)	.
Married	0.012	0.144**	0.014	0.131*	0.009	0.133	0.009	0.132
	(0.021)	(0.073)	(0.019)	(0.068)	(0.028)	(0.114)	(0.029)	(0.119)
Han	0.023	.	0.002	.	0.018	.	0.018	.
	(0.015)	.	(0.017)	.	(0.014)	.	(0.017)	.
Household size	−0.008	−0.026*	−0.005	−0.024*	−0.005	−0.021	−0.005	−0.021
	(0.005)	(0.013)	(0.005)	(0.013)	(0.005)	(0.018)	(0.006)	(0.018)
Primary school	−0.004	0.040	−0.005	0.040	−0.004	0.039	−0.004	0.039
	(0.017)	(0.047)	(0.016)	(0.044)	(0.024)	(0.074)	(0.026)	(0.071)
Junior high school	−0.007	0.041	−0.017	0.026	−0.011	0.043	−0.011	0.043
	(0.018)	(0.057)	(0.017)	(0.054)	(0.026)	(0.090)	(0.023)	(0.095)
Low household income	−0.023	−0.022	−0.018	−0.025	−0.019	−0.025	−0.019	−0.027
	(0.015)	(0.030)	(0.014)	(0.028)	(0.018)	(0.038)	(0.021)	(0.047)
High household income	−0.011	0.036	−0.007	0.023	−0.008	0.036	−0.008	0.034
	(0.015)	(0.033)	(0.014)	(0.031)	(0.019)	(0.041)	(0.017)	(0.032)
Number of children	0.019**	−0.026	0.017**	−0.026	0.020**	−0.031	0.019*	−0.029
	(0.009)	(0.027)	(0.008)	(0.025)	(0.010)	(0.036)	(0.011)	(0.037)
Number of elderly members	0.019**	0.015	0.014*	−0.000	0.019*	0.015	0.019**	0.015
	(0.008)	(0.023)	(0.007)	(0.022)	(0.010)	(0.028)	(0.009)	(0.032)
Number of members with chronic diseases	−0.014	−0.007	−0.018	0.020	−0.023	−0.004	−0.023	−0.009
	(0.019)	(0.048)	(0.018)	(0.045)	(0.023)	(0.072)	(0.024)	(0.074)
Village population density	0.026***	0.113***	0.006	0.043**	0.022***	0.137***	0.022***	0.136***
	(0.005)	(0.020)	(0.005)	(0.020)	(0.007)	(0.026)	(0.006)	(0.028)
Log(village urbanicity)	−0.021	0.432***	−0.003	0.075	−0.004	0.243	−0.004	0.241
	(0.026)	(0.101)	(0.026)	(0.100)	(0.031)	(0.160)	(0.035)	(0.160)
Any health facility in the village	0.050	0.097	0.008	0.030	0.018	0.066	0.018	0.067
	(0.019)	(0.041)	(0.019)	(0.039)	(0.020)	(0.046)	(0.020)	(0.054)
Physician density	0.096***	0.034	0.023	0.010	0.062***	0.016	0.062***	0.019
	(0.033)	(0.052)	(0.314)	(0.049)	(0.007)	(0.421)	(0.008)	(0.561)
Village had health insurance in 2000	−0.026**	.	−0.007	.	−0.014	.	−0.013	.
	(0.013)	.	(0.015)	.	(0.014)	.	(0.014)	.
Wave 2006	0.163***	−0.039	0.049*	−0.104	0.194***	−0.030	0.194***	−0.038
	(0.026)	(0.218)	(0.026)	(0.208)	(0.052)	(0.574)	(0.044)	(0.700)
Wave 2009	0.352***	−0.129	0.099***	−0.253	0.251***	−0.221	0.251***	−0.242
	(0.024)	(0.445)	(0.026)	(0.514)	(0.044)	(1.465)	(0.049)	(1.773)
Control of household fixed effect	No	Yes	No	Yes	No	Yes	No	Yes
Control of provincial dummies	Yes	–	Yes	–	Yes	–	Yes	–
R^2 within	0.1975	0.2485	0.3220	0.3407	0.2138	0.2655	0.2138	0.2655
R^2 between	0.0918	0.0007	0.2086	0.0005	0.1553	0.0001	0.1553	0.0001
R^2 overall	0.1208	0.0000	0.2422	0.0034	0.1714	0.0001	0.1714	0.0001
Wald chi^2/F statistic	445.05	14.79	1032.21	21.87	1741.56	391.25	1741.56	307.48
N	3262	1620	3261	1620	3261	1620	3261	1620

Notes: (1) In columns (1)–(4), cluster-robust standard errors are reported in parenthesis; (2) standard errors in columns (5)–(8) are based on 500 bootstraps.
* Statistically significant at the 10 percent.
** Statistically significant at the 5 percent.
*** Statistically significant at the 1 percent.

unobserved characteristics or common environment, but such correlation of age cannot be driven by peer effects. If our exclusion conditions are valid, our two-step method would remove this correlation. As expected, when we regress the age of household head on average age of household heads in the village, observed household and village-level characteristics, a set of regional and time dummies (i.e. using the same specification and sample as our main regression), the OLS estimate of the coefficient on average age is positive and significant at the 1 percent level. However, when we apply our two-step procedure using peers' health status as the exclusion condition, the estimated coefficient of average age in the second

Table 4
Nonlinear social effects of NCMS enrollment.

	Two-step estimation			
	Use quadratic forms		Use linear splines	
	RE (1)	FE (2)	RE (3)	FE (4)
Peer enrollment in the village	3.148***	3.613***		
	(0.535)	(0.887)		
Squared peer enrollment	−1.656***	−2.049***		
	(0.358)	(0.550)		
Peer enrollment in the village: 0–0.6			1.394***	1.458***
			(0.420)	(0.453)
Peer enrollment in the village: 0.6–0.9			0.709***	0.659**
			(0.138)	(0.328)
Peer enrollment in the village: 0.9 and above			−0.295	−0.731
			(0.254)	(0.514)
Wave 2006	0.154***	0.080	0.156***	0.076
	(0.034)	(0.073)	(0.042)	(0.050)
Wave 2009	0.202***	0.089	0.201***	0.077
	(0.039)	(0.071)	(0.044)	(0.063)
Control of household characteristics	Yes	Yes	Yes	Yes
Control of household fixed effect	No	Yes	No	Yes
Control of village characteristics	Yes	Yes	Yes	Yes
Control of provincial dummies	Yes	–	Yes	–
N	3261	1620	3261	1620

Notes: Standard errors based on 500 bootstraps are reported in parenthesis.
** Statistically significant at the 5 percent.
*** Statistically significant at the 1 percent.

step estimation is statistically insignificant, with or without control for household fixed effects or village fixed effects (see Table A2). This test yields similar results as the one in Duflo and Saez (2002), and suggests that our exclusion condition is valid and can be successful in removing simultaneity in households' NCMS enrollment decisions in a particular village.

The last test to our exclusion condition is to divide the villagers within a village into sub-groups, and to estimate peer effects within and between sub-groups. The idea for this test is that, if the co-villagers' health conditions cannot serve as the valid exclusion restriction, the two-step method would fail to purge the spurious correlation of the NCMS take-up behaviors within the village. Assuming that such correlated effects are in part common to the whole village, we should have found both significant within-subgroup effects and significant cross-subgroup effects in the sub-group decomposition (Duflo and Saez, 2002). This exercise also supports the validity of our exclusion restriction, and we will discuss results thoroughly in Section 5.2.

In Table 4, we investigate the possible non-linearity of social effects in NCMS enrollment. We first add a quadratic term for peer enrollment in columns (1) and (2) and find that it is significant and negative. It implies that social effect exhibits a concave pattern, or even an inverted U shape. The estimated turning point is 0.88, above the 60th percentile of the estimated peer enrollment. While it is possible to tell stories about negatively correlated decisions among the villagers,[22] we suspect that this kind of scenarios could reflect the reality of the NCMS.

To avoid erroneously accepting the hypothesis of an inverse U-shaped relationship, we conduct linear spline regressions with two discontinuity points, 0.6 and 0.9, corresponding to the 20th and 70th percentiles of peer enrollment. Consistent with the results from the quadratic specification, the results in columns (3) and (4) show that the social effect is approximately 1.46 in villages with peer enrollment rates below 60 percent, decreases to 0.66 when the peer enrollment rate is between 60 and 90 percent, and becomes statistically indistinguishable from 0 when the peer enrollment rate exceeds 90 percent. The results indicate that the social effects operate in a concave manner, but not an inverse U shape. The concavity may suggest that at an early stage, information is more valuable and the villagers are more susceptible to peer influence. At a later stage, as the information diffuses, the take-up behavior of peers becomes less informative, and those who could be easily affected by the peers were already in the program.

5.2. Importance of time-variant unobserved common factors

Although our two-step approach can deal with simultaneity and control for time-invariant unobservables and time-variant unobservables with common time trend, there is still a concern that other time-varying unobserved heterogeneity

[22] For example, when most residents in the village are enrolled in NCMS, they may express dissatisfaction in the communications with their co-villagers. Then those uninsured peers may choose not to participate in NCMS, and some enrolled peers may even choose to quit the program. As a result, the villagers' decisions may be negatively correlated.

Table 5
Social effects from different villages and counties.

	Two-step estimation							
	Random effect				Fixed effect			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Peer enrollment in the village	0.612***			0.736***	0.502***			0.563**
	(0.058)			(0.096)	(0.109)			(0.284)
Peer enrollment in other villages of the county		0.322***		0.003		0.132		−0.160
		(0.065)		(0.103)		(0.136)		(0.297)
Peer enrollment in other counties of the province			−0.077	0.201			0.079	−0.005
			(0.146)	(0.142)			(0.341)	(0.243)
Control of household characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control of household fixed effect	No	No	No	No	Yes	Yes	Yes	Yes
Control of village characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control of provincial dummies	Yes	Yes	Yes	Yes	–	–	–	–
Control of wave dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3261	3225	3029	2991	1620	1614	1308	1302

Notes: Standard errors based on 500 bootstraps are reported in parenthesis.
** Statistically significant at the 5 percent.
*** Statistically significant at the 1 percent.

is responsible for our findings. Therefore, we conduct two robustness checks to falsify the possibility that the time-variant common unobservables drive the social effect established in the previous subsection.

First, the quality of the NCMS program may lead to correlated decisions of rural households in the same county as well as in the same village. In Table 5, we separately estimate the social effects from peers in the same village, in other villages of the same county, and in other counties of the same province. The results show that the estimated social effects decline in spatial distance, implying that households are influenced more by their peers living in the same village than by others living in different villages or counties. This suggests that the estimates are most likely to capture the role of causal peer effects, and not the effect of the common unobservables at the county level; otherwise, we should at least observe significant effects from peer enrollments in other villages of the same county, as they share similar unobserved NCMS policy characteristics.

Moreover, the findings are also consistent with the theory of social learning. It implies that the strength of the social effect should be greater for household pairs with closer spatial proximity (Bertrand et al., 2000; Munshi and Myaux, 2006), so that information can be transmitted through formal or casual/word-of-mouth communications. Each village in China is a closely-knit, long-established social network, and individuals usually tend to have more social interactions with others within the village than across villages.

Second, the similarity of households' enrollment decisions may also be driven by village-level common unobservables, e.g., a local official information campaign, or similar unobserved preferences of the villagers. We divide households into different subgroups within villages according to their observable demographic and socioeconomic characteristics and estimate the different social effects among subgroups. This analysis can help us separate the causal peer effect from the influence of village-level common unobservables (Duflo and Saez, 2002; Munshi and Myaux, 2006) and capture the pattern of peer effects.

Based on the conjecture that individuals may be more likely to interact with co-villagers who share common observable characteristics, we should observe stronger social effects within subgroups than across subgroups in the village (Duflo and Saez, 2002; Sorensen, 2006). If individuals' enrollment decisions are influenced by their observations of others' behavior, there may be opinion leaders in rural villages who appear to have expertise and the ability to make informed NCMS enrollment decisions (Bikhchandani et al., 1998). This analysis can determine the observable characteristics associated with occupying a leadership role.

Table 6 presents the estimated social effects from co-villagers within subgroups for households in the full sample and in each subgroup. We find significant symmetric and asymmetric social effects. The former is consistent with our prior conjecture, showing that the enrollment behavior of male (or Han) household heads is significantly affected by other male (or Han) household heads, but not by female (or minority) heads. Similar to Chen et al. (2010), we also find that younger heads (age 18–55) are significantly affected by those aged 55 and above, and female heads are significantly influenced by male heads; whereas the reverse effects are close to zero and within-group effects for these households are nearly absent. These findings imply that, on average, the behaviors of the older, Han, male heads have the strongest effect on rural residents in the village.

Moreover, the results in panel 4 indicate that household heads with a low education level (below the 30th percentile in the village) are significantly affected by the behavior of household heads with a medium education level (between the 30th and 70th percentiles in the village). Similarly, panel 5 of Table 6 shows that households with low (middle) income levels respond significantly to the enrollment rate of households with middle (high) incomes in the same village. We find no significant within-income-group or within-education-group effects. These findings are consistent with the theory of social learning. Households with low socioeconomic status may find the decisions of co-villagers with middle socioeconomic status more

Table 6
Social effects from different subgroups in the village.

Two-step estimation with fixed effect	(1) Full sample	(2) Age 18–54	(3) Age 55 and above
Panel 1: group by household head's age in the village			
Peer enrollment in group age 18–54	0.156	0.108	0.219
	(0.139)	(0.209)	(0.360)
Peer enrollment in group age 55 and above	0.378**	0.434***	0.290
	(0.162)	(0.170)	(0.374)
N	1572	779	630

Two-step estimation with fixed effect	(1) Full sample	(2) Han	(3) Minorities
Panel 2: group by household head's ethnicity in the village			
Peer enrollment in Han group	0.296**	0.456***	0.168
	(0.128)	(0.136)	(0.256)
Peer enrollment in minorities' group	0.120	0.094	−0.063
	(0.104)	(0.090)	(0.602)
N	1600	1262	338

Two-step estimation with fixed effect	(1) Full sample	(2) Male	(3) Female
Panel 3: group by household head's gender in the village			
Peer enrollment in male group	0.511**	0.385**	1.190*
	(0.203)	(0.173)	(0.523)
Peer enrollment in female group	0.028	0.092	−0.207
	(0.141)	(0.190)	(0.757)
N	1405	1224	181

Two-step estimation with fixed effect	(1) Full sample	(2) Below 30th percentile	(3) Between 30th and 70th percentile	(4) Above 70th percentile
Panel 4: group by household head's education level in the village				
Peer enrollment in group with low education	−0.005	−0.156	0.308	0.127
	(0.140)	(0.501)	(0.261)	(0.246)
Peer enrollment in group with mid education	0.030	0.783*	−0.205	0.112
	(0.274)	(0.398)	(0.279)	(0.222)
Peer enrollment in group with high education	0.308	−0.026	0.367	−0.075
	(0.241)	(0.723)	(0.308)	(0.281)
N	1205	172	274	407

Two-step estimation with fixed effect	(1) Full sample	(2) Below 30th percentile	(3) Between 30th and 70th percentile	(4) Above 70th percentile
Panel 5: group by household income level in the village				
Peer enrollment in group with low HH income	0.036	−0.499	0.258	0.092
	(0.156)	(0.716)	(0.623)	(0.123)
Peer enrollment in group with mid HH income	0.154	0.647**	−0.645	0.404
	(0.209)	(0.276)	(0.595)	(0.286)
Peer enrollment in group with high HH income	0.315***	0.043	0.510*	0.024
	(0.098)	(0.504)	(0.297)	(0.289)
N	1619	216	294	247

Notes: (1) Standard errors based on 500 bootstraps are reported in parenthesis. (2) Other regressors include all explanatory variables listed in Table 3, unobserved household-specific fixed effect, and constant, which are not reported here.
* Statistically significant at the 10 percent.
** Statistically significant at the 5 percent.
*** Statistically significant at the 1 percent.

informative, due to their lack of relevant knowledge and their limited access to information resources. However, they are not significantly affected by those with high socioeconomic status in the village, partly because they lack common backgrounds and have fewer social interactions.

Overall, the results in Table 6 imply that wealthier, relatively well-educated, older, Han, male household heads tend to be opinion leaders. We do not find the presence of both within-subgroup effects and cross-subgroup effects in any regression specification in Table 6. This clear pattern provides supporting evidence for the causal peer effects from our two-step procedure, and is inconsistent with the hypothesis of village-specific common unobservables. Moreover, as discussed in Section 5.1, the findings in Table 6 also add further evidence to support the plausibility of our identification condition.

Table 7
Social effects by NCMS implementation time.

Two-step estimation	Villages with NCMS newly introduced in each wave			All villages
	CHNS 2004 (1)	CHNS 2006 (2)	CHNS 2009 (3)	CHNS 2009 (4)
Peer enrollment in the village	1.397*** (0.483)	0.874*** (0.123)	0.560*** (0.174)	0.667*** (0.160)
Peer enrollment × NCMS introduced in wave 2006				−0.381** (0.184)
Peer enrollment × NCMS introduced in wave 2004				−0.686** (0.349)
NCMS introduced in wave 2009				Reference
NCMS introduced in wave 2006				0.345** (0.170)
NCMS introduced in wave 2004				0.639** (0.308)
Control of household characteristics	Yes	Yes	Yes	Yes
Control of household fixed effect	No	No	No	No
Control of village characteristics	Yes	Yes	Yes	Yes
Control of provincial dummies	Yes	Yes	Yes	Yes
Control of wave dummies	–	–	–	–
N	233	819	866	2162

Notes: Standard errors based on 500 bootstraps are reported in parenthesis.
** Statistically significant at the 5 percent.
*** Statistically significant at the 1 percent.

5.3. *Social leaning as the main mechanism*

In the subsection, we investigate whether the mechanism underlying the causal peer effects on NCMS enrollment established above is social learning or other plausible alternative channels, for example, the desire to conform. The theory of social learning predicts that social learning is more important in the demand for complex or unfamiliar products. In other words, if the peer effect captures information sharing, it should have a greater impact on individual enrollment decision in villages that receive relatively less health insurance information. We test this proposition with three specifications.

According to the implementation timing of the NCMS, we classify the sample counties into three groups: the NCMS programs introduced in the 2004, 2006 and 2009 waves. In the first specification, we estimate the social effects for only those counties where the NCMS was newly established in each wave.[23] As shown in columns (1)–(3) of Table 7, all of the social effects are significant in each wave. Peer enrollment has the largest impact in the 2004 wave, when the NCMS was new to all rural residents. However, this peer effect reduces to less than half in the 2009 wave, when individuals had already learned more about the NCMS from pilot counties before it was implemented in their own counties.

In the second specification, we examine the different sizes of the social effects in counties that had the NCMS for different lengths of time. Using the CHNS 2009, we include interaction terms between peer enrollment and the NCMS duration. Column (4) of Table 7 shows that social effects are larger in villages where the NCMS was implemented more recently, and social effects decrease significantly along with the duration of the NCMS implementation. These findings provide evidence that social learning plays a more important role when people are unfamiliar with the NCMS.

Modern information and communication technologies, such as the Internet, may reduce the strength of social learning within the village, since these technologies provide alternative channels for information dissemination besides peer interaction (Bikhchandani et al., 1998; Chen et al., 2010). In the third specification, we include interactions between peer enrollment and the development of information technology in each village, measured by overall communication scores and two binary variables indicating access to convenient internet and cell phone service in the village. As shown in Table 8, the interaction terms are negative and statistically significant. These estimates suggest that individuals are influenced less by co-villagers when they have more convenient access to modern communication systems, i.e., alternative informational channels, which is fully consistent with the social-learning hypothesis.

6. Policy implications

Social effects have important policy implications for the long run success of the NCMS. First, they can alleviate the issue of adverse selection in NCMS participation. To illustrate this empirically, in column (1) of Table 9 we first add interactions between the social effects and indicators of the health status of household head and household members. The results indicate that social effects are stronger for households without chronic diseases than for those with chronic diseases. Moreover,

[23] As we estimate the social effects using cross sectional data from different waves of CHNS, we cannot control for household fixed effects in Table 7.

Table 8
Social effects by communication levels of the village.

Two-step estimation with fixed effect	Interacted with the overall communication level of the village (1)	Interacted with access to convenient internet service in the village (2)	Interacted with access to convenient cell phone service in the village (3)
Peer enrollment in the village	1.274***	0.682***	0.959***
	(0.405)	(0.229)	(0.240)
Peer enrollment × communications score	−0.140***		
	(0.074)		
Peer enrollment × convenient internet service		−0.423**	
		(0.214)	
Peer enrollment × convenient cell phone service			−0.539***
			(0.207)
Communications score of the village	0.118**		
	(0.060)		
Access to convenient internet service		0.370**	
		(0.169)	
Access to convenient cell phone service			0.415***
			(0.169)
Control of household characteristics	Yes	Yes	Yes
Control of household fixed effect	Yes	Yes	Yes
Control of village characteristics	Yes	Yes	Yes
Control of wave dummies	Yes	Yes	Yes
N	1620	1620	1620

Notes: Standard errors based on 500 bootstraps are reported in parenthesis.
** Statistically significant at the 5 percent.
*** Statistically significant at the 1 percent.

Table 9
Social effects and adverse selection.

Two-step estimation with fixed effect	(1) Full sample	(2) Full sample	(3) No chronic disease	(4) With chronic disease
Panel 1: interacted with/group by household head's chronic disease status				
Peer enrollment in the village	0.529***			
	(0.179)			
Peer enrollment × household head has chronic disease	−0.437**			
	(0.213)			
Household head has chronic disease	0.360**			
	(0.127)			
Peer enrollment in subgroup without chronic disease		0.728***	0.809***	0.889
		(0.216)	(0.224)	(0.719)
Peer enrollment in subgroup with chronic disease		−0.062	−0.149	−0.463
		(0.135)	(0.131)	(0.455)
N	1620	1062	883	77
Panel 2: interacted with/group by household member's chronic disease status				
Peer enrollment in the village	0.560***			
	(0.144)			
Peer enrollment × household member has chronic disease	−0.378**			
	(0.185)			
Household member has chronic disease	0.465**			
	(0.227)			
Peer enrollment in subgroup without chronic disease		0.541***	0.672***	0.554**
		(0.160)	(0.243)	(0.244)
Peer enrollment in subgroup with has chronic disease		0.023	−0.055	0.157
		(0.115)	(0.158)	(0.496)
N	1620	1364	952	149

Notes: (1) Standard errors based on 500 bootstraps are reported in parenthesis. (2) Other regressors include all explanatory variables listed in Table 3, unobserved household-specific fixed effect, and constant, which are not reported here.
** Statistically significant at the 5 percent.
*** Statistically significant at the 1 percent.

Table 10
Social effect and financial need.

Two-step estimation with fixed effect	Interacted with household income (1)	Interacted with village urbanicity score (2)
Peer enrollment in the village	0.256**	0.339**
	(0.117)	(0.157)
Peer enrollment × low household income	0.620***	
	(0.224)	
Peer enrollment × high household income	0.046	
	(0.245)	
Peer enrollment × low urbanicity index		0.639**
		(0.272)
Peer enrollment × high urbanicity index		−0.165
		(0.240)
Lowest 30 percent	−0.495***	−0.523**
	(0.178)	(0.217)
Highest 30 percent	0.003	−0.165
	(0.209)	(0.240)
Control of household characteristics	Yes	Yes
Control of household fixed effect	Yes	Yes
Control of village characteristics	Yes	Yes
Control of wave dummies	Yes	Yes
N	1620	1620

Notes: Standard errors based on 500 bootstraps are reported in parenthesis.
** Statistically significant at the 5 percent.
*** Statistically significant at the 1 percent.

when we estimate social effects for subgroups with or without chronic disease, we also find that both healthy and unhealthy households are significantly influenced by the average enrollment of their healthy co-villagers. This finding suggests that enrolling healthier households is important for the sustainability of the NCMS, not only because of its direct effect on risk pooling, but also because of its indirect effect through social influence.

Designed to reduce the poverty associated with poor health, the NCMS is more meaningful for poor households and poor villages. With less relevant knowledge and limited information access, poor households are more likely to face information barriers in their enrollment decisions. The study of social effects helps us to better understand how individuals with different backgrounds obtain information through social learning, especially for the poor. In Table 5, we have already shown that poor households are significantly influenced by the behaviors of more affluent co-villagers. Furthermore, in Table 10 we include interactions between the peer effects and indicators for income groups and indicators for the community urbanicity index in the regressions. The urbanicity index reflects development on a wide range of village aspects, including infrastructure, education, and medical services. Households living in villages with higher urbanicity index scores may enjoy better resources in terms of education, information, and other aspects of acquiring necessary information about the NCMS. As expected, the results show that social effect is more influential for households with low household income and those living in relatively less developed villages. The significant negative coefficients on the low household income and low community urbanicity indicators suggest that without the role of social learning, households that are poor or from poor villages may have lower NCMS participation rates.

7. Conclusions

In this paper, we investigate the importance of social learning in household NCMS enrollment decisions in rural China by modeling households' enrollment decisions as a static game of incomplete information. In our model, households make their enrollment decisions based on their characteristics (some of them are private information), village characteristics, as well as other households' enrollment decisions. We find that the NCMS enrollment probability of an individual household would increase by 5 percentage points if the enrollment rate of other households in the same village were to increase by 10 percentage points. From a policy perspective, such peer effects are equivalent to a social multiplier effect of 1.9 at the village level, based on the computation method proposed by Glaeser et al. (2003).

We discuss and clarify how the identification problems can be resolved in order to establish a causal relationship between social learning and household enrollment behavior. First, we employ the two-step approach proposed by Bajari et al. (2010), together with household-level fixed effects, to control for the endogeneity of the village-level peer enrollment rate. This estimation strategy draws on the growing literature on estimating static discrete-choice games in industrial organization in which one agent's payoff is affected by other agents' decisions, and can deal with simultaneity and unobserved time-invariant heterogeneity. Moreover, two robustness checks help to rule out the potential confounding influence of time-varying common unobservables in our two-step estimations, and provide further support for the establishment of causal peer effects. Second, using the rich information in our dataset, we conduct several specification tests to show that the mechanism for social effects in NCMS enrollment is primarily social learning. Specifically, we show that the role of social effects are more salient when individuals are unfamiliar with NCMS, and their influence increases with close geographical proximity, which is fully consistent with the theory of social learning. Moreover, we also find that the importance of social learning from co-villagers decreases significantly with the development of alternative information channels.

We add to the literature by providing empirical evidence for asymmetric peer effects in the setting of health insurance enrollment. We find that healthier, older, Han, male household heads with higher education and income levels tend to be opinion leaders; they have a significant influence on households with low socioeconomic status. This is consistent with the empirical finding in other contexts. For example, Nair et al. (2010) find that research-active physicians significantly influence the behavior of other physicians but not vice versa. Thus, our results suggest that targeting opinion leaders in rural villages with an information campaign may have economically significant social multiplier effects on social programs.

As a related finding to the existence of opinion leaders, our evidence also suggests that low income families and families living in relatively poor villages were more influenced by social learning, which may have important implications for the implementation and the evaluation of social programs.

Finally, our data allow us to investigate peer effects at different stages of the NCMS program: from inception, to expansion, and to full coverage. We find that the importance of the peer effects varies with the evolution of the program.

Appendix A.

Table A1
The first stage results with different specifications.

	Linear first stage		Semiparametric first stage			
	(1)	(2)	(3)	(4)	(5)	(6)
First stage estimation						
Whether household head has chronic diseases	0.124**	0.077**	0.059**	0.053**	0.044**	0.023*
	(0.062)	(0.032)	(0.028)	(0.025)	(0.020)	(0.013)
Number of household members with chronic diseases	0.036*	0.043				
	(0.022)	(0.028)				
Number of household members with chronic diseases Knot 1			0.735*	0.506	1.047	0.773
			(0.428)	(0.365)	(1.529)	(0.561)
Number of household members with chronic diseases Knot 2			0.321	0.101	0.511	0.316
			(0.772)	(0.423)	(0.399)	(0.245)
Number of household members with chronic diseases Knot 3			−0.031	−0.058	0.108	0.410
			(0.183)	(0.101)	(0.548)	(0.254)
Household fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
County-year interactions	No	Yes	No	Yes	No	Yes
3rd-order splines of other household characteristics	No	No	No	No	Yes	Yes
Adjusted R^2	0.283	0.289	0.290	0.299	0.300	0.312
Test of joint significance of household health conditions						
F statistics	3.08	3.19	2.63	2.50	2.45	2.40
P-Value	0.046	0.042	0.034	0.041	0.044	0.048
Fixed effect estimation for the second stage						
Peer enrollment in the village	0.452***	0.503***	0.498***	0.509***	0.483***	0.503***
	(0.119)	(0.147)	(0.139)	(0.169)	(0.125)	(0.198)
Control of household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Control of household fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Control of village characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Control of wave dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	1620	1620	1620	1620	1620	1620

Notes: (1) Column (3) presents our first-stage estimates for the main specification in Table 3. (2) In columns (5) and (6), the first stage estimations also include 3rd-order splines of household head's age and years of education, household's income, number of children and elder people in the households, respectively, as additional exclusion restrictions. (3) The second stage estimation of each specification includes all the control variables as in Table 3. (4) Standard errors are based on 500 bootstraps.

* Statistically significant at the 10 percent.

** Statistically significant at the 5 percent.

*** Statistically significant at the 1 percent.

Table A2
Testing our identification assumption with the age of household head.

	Use simple average		Two-step estimation		
Control of household fixed effect in the first step			No	No	Yes
Control of village fixed effect in the first step			No	Yes	–
	Use simple average		Two-step estimation		
	RE	FE	RE	RE	FE
	(1)	(2)	(3)	(4)	(5)
Peer age in the village	0.153***	0.111*	0.191	−0.862	0.571
	(0.051)	(0.065)	(0.490)	(0.541)	(1.138)
Chronic disease	2.414***	2.389**	2.368***	2.108***	2.355**
	(0.784)	(1.000)	(0.781)	(0.794)	(0.949)
Female	2.057***	4.448**	2.066***	1.943**	4.391**
	(0.783)	(1.953)	(0.773)	(0.812)	(1.939)
Married	−4.815***	−3.282***	−4.830***	−4.684***	−3.271***
	(0.592)	(0.917)	(0.598)	(0.605)	(0.917)
Han	−0.357	5.105	−0.430	−0.983	5.016
	(0.730)	(8.605)	(0.796)	(1.065)	(8.423)
Household size	0.250**	0.091	0.244*	0.262**	0.082
	(0.126)	(0.110)	(0.131)	(0.126)	(0.108)
Schooling years	−0.907***	−0.504***	−0.910***	−0.938***	−0.505***
	(0.079)	(0.144)	(0.080)	(0.081)	(0.145)
Low household income	0.680***	0.184	0.711***	0.634**	0.227
	(0.261)	(0.221)	(0.259)	(0.251)	(0.224)
High household income	−0.792***	−0.310	−0.812***	−0.715***	−0.316
	(0.247)	(0.264)	(0.248)	(0.263)	(0.265)
Number of children	−1.654***	−0.026	−1.676***	−1.664***	−0.072
	(0.277)	(0.327)	(0.279)	(0.287)	(0.338)
Number of elderly members	3.435***	0.440**	3.434***	3.409***	0.415*
	(0.298)	(0.203)	(0.300)	(0.306)	(0.212)
Number of members with chronic diseases	0.559	−1.041*	0.591	0.660	−1.013*
	(0.529)	(0.563)	(0.524)	(0.535)	(0.533)
Village population density	−0.143	−0.062	−0.179	−0.150	−0.069
	(0.145)	(0.187)	(0.163)	(0.247)	(0.201)
Log(village urbanicity)	−0.519	0.124	−1.003	−0.669	−0.389
	(0.735)	(0.883)	(0.815)	(1.108)	(0.934)
Any health facility in the village	0.881**	0.864*	0.829	0.898	0.804
	(0.437)	(0.490)	(0.511)	(0.634)	(0.534)
Physician density	0.016	−0.046	−0.130	−0.145	−0.195
	(0.102)	(0.107)	(0.100)	(0.115)	(0.129)
Village had health insurance in 2000	−0.221		−0.327	7.860**	
	(0.411)		(0.487)	(3.709)	
Wave 2006	3.905***	1.993***	3.735***	6.002***	0.978
	(0.457)	(0.496)	(1.099)	(1.186)	(2.145)
Wave 2009	5.294***	4.236***	4.896**	9.675***	1.902
	(0.524)	(0.630)	(2.275)	(2.427)	(5.074)
Control of household fixed effect	No	Yes	No	No	Yes
Control of village fixed effect	No	–	No	Yes	–
Control of provincial dummies	Yes	–	Yes	–	–
N	3261	1620	3261	3261	1620

Notes: (1) cluster-robust standard errors are reported in parenthesis. (2) In the first stage estimation of column (3), we regress household head's age on the indicator whether household head has chronic diseases, number of household members with chronic diseases, and year dummies. We add village fixed effect in the first stage estimation of column (4), and add household fixed effect in the first stage estimation of column (5).

* Statistically significant at the 10 percent.
** Statistically significant at the 5 percent.
*** Statistically significant at the 1 percent.

References

Aguirregabiria, V., Mira, P., 2002. Swapping the nested fixed point algorithm: a class of estimators for discrete Markov decision models. Econometrica 70 (4), 1519–1543.

Aguirregabiria, V., Mira, P., 2007. Sequential estimation of dynamic discrete games. Econometrica 75 (1), 1–53.

Aizer, A., 2007. Public health insurance, program take-up, and child health. Review of Economics and Statistics 89 (3), 400–415.

Bajari, P., Benkard, C.L., Levin, J., 2007. Estimating dynamic models of imperfect competition. Econometrica 75 (5), 1331–1370.

Bajari, P., Hong, H., Krainer, J., Nekipelov, D., 2010. Estimating static models of strategic interactions. Journal of Business & Economic Statistics 28 (4), 469–482.

Bandura, A., 1977. Social Learning Theory. Prentice Hall, New York.

Bertrand, M., Luttmer, E.F.P., Mullainathan, S., 2000. Network effects and welfare cultures. Quarterly Journal of Economics 115 (3), 1019–1055.

Bikhchandani, S., Hirshleifer, D., Welch, I., 1998. Learning from the behavior of others: conformity, fads, and informational cascades. Journal of Economic Perspectives 12 (3), 151–170.
Brown, P.H., De Brauw, A., Du, Y., 2009. Understanding variation in the design of China's new co-operative medical system. The China Quarterly 198 (1), 304–329.
Brown, P.H., Bulte, E., Zhang, X., 2011. Positional spending and status seeking in rural China. Journal of Development Economics 96 (1), 139–149.
Cai, H., Chen, Y., Fang, H., 2009. Observational learning: evidence from a randomized natural field experiment. American Economic Review 99 (3), 864–882.
Cameron, A.C., Trivedi, P.K., Milne, F., Piggott, J., 1988. A microeconometric model of the demand for health care and health insurance in Australia. Review of Economic Studies 55 (1), 85–106.
Chen, Y., Jin, G.Z., Yue, Y., 2010. Peer migration in China. National Bureau of Economic Research Working Paper Series, No. 15671.
Congressional Budget Office, 2005. The Price Sensitivity of Demand for Nongroup Health Insurance. Congressional Budget Office, Washington DC, USA.
Craig, P., 1991. Costs and benefits: a review of research on take-up of income-related benefits. Journal of Social Policy 20 (4), 537–565.
Currie, J., 2004. The take up of social benefits. National Bureau of Economic Research Working Paper Series, No. 10488.
Dahl, G.B., Løken, K.V., Mogstad, M., 2012. Peer effects in program participation. National Bureau of Economic Research Working Paper Series, No. 18198.
Duflo, E., Saez, E., 2002. Participation and investment decisions in a retirement plan: the influence of colleagues' choices. Journal of Public Economics 85 (1), 121–148.
Duflo, E., Saez, E., 2003. The role of information and social interactions in retirement plan decisions: evidence from a randomized experiment. Quarterly Journal of Economics 118 (3), 815–842.
Feng, X., Tang, S., Bloom, G., Segall, Ma., Gu, X., 1995. Cooperative medical schemes in contemporary rural China. Social Science & Medicine 41 (8), 1111–1118.
Foster, A.D., Rosenzweig, M.R., 1995. Learning by doing and learning from others: human capital and technical change in agriculture. Journal of Political Economy 103 (6), 1176–1209.
Glaeser, E.L., Scheinkman, J.A., Sacerdote, B.I., 2003. The social multiplier. Journal of the European Economic Association 1 (2/3), 345–353.
Gruber, J., Poterba, J., 1994. Tax incentives and the decision to purchase health insurance: evidence from the self-employed. Quarterly Journal of Economics 109 (3), 701–733.
Hong, H., Kubik, J.D., Stein, J.C., 2004. Social interaction and stock-market participation. Journal of Finance 59 (1), 137–163.
Jones-Smith, J.C., Popkin, B.M., 2010. Understanding community context and adult health changes in China: development of an urbanicity scale. Social Science & Medicine 71 (8), 1436–1446.
Kleven, H.J., Kopczuk, W., 2011. Transfer program complexity and the take-up of social benefits. American Economic Journal: Economic Policy 3 (1), 54–90.
Krueger, A.B., Kuziemko, I., 2013. The demand for health insurance among uninsured Americans: results of a survey experiment and implications for policy. Journal of Health Economics 32 (5), 780–793.
Lei, X., Lin, W., 2009. The New Cooperative Medical Scheme in rural China: does more coverage mean more service and better health? Health Economics 18 (S2), S25–S46.
Li, S., Liu, Y., Deininger, K., 2013. How important are endogenous peer effects in group lending? Estimating a static game of incomplete information. Journal of Applied Econometrics 28 (5), 864–882.
Liu, Y., 2004a. China's public health-care system: facing the challenges. Bulletin of the World Health Organization 82 (7), 532–538.
Liu, Y., 2004b. Development of the rural health insurance system in China. Health Policy and Planning 19 (3), 159–165.
Liu, X., Cao, H., 1992. China's Cooperative Medical System: its historical transformations and the trend of development. Journal of Public Health Policy 13 (4), 501–511.
Mangyo, E., Park, A., 2011. Relative deprivation and health: which reference groups matter? Journal of Human Resources 46 (3), 459–481.
Manski, C.F., 1993. Identification of endogenous social effects: the reflection problem. Review of Economic Studies 60 (3), 531–542.
Manski, C.F., 2000. Economic analysis of social interactions. Journal of Economic Perspectives 14 (3), 115–136.
Mao, Z., 2005. Pilot program of NCMS in China: system design and progress. World Bank Report on China Rural Health Study.
Marquis, M.S., Long, S.H., 1995. Worker demand for health insurance in the non-group market. Journal of Health Economics 14 (1), 47–63.
Matzkin, R.L., 1992. Nonparametric and distribution-free estimation of the binary threshold crossing and the binary choice models. Econometrica 60 (2), 239–270.
Moffitt, R., 1983. An economic model of welfare stigma. American Economic Review 73 (5), 1023–1035.
Mundlak, Y., 1978. On the pooling of time series and cross section data. Econometrica 46 (1), 69–85.
Munshi, K., 2004. Social learning in a heterogeneous population: technology diffusion in the Indian Green Revolution. Journal of Development Economics 73 (1), 185–213.
Munshi, K., Myaux, J., 2006. Social norms and the fertility transition. Journal of Development Economics 80 (1), 1–38.
Nair, H.S., Manchanda, P., Bhatia, T., 2010. Asymmetric social interactions in physician prescription behavior: the role of opinion leaders. Journal of Marketing Research 47 (5), 883–895.
Newey, W.K., 1994. The asymptotic variance of semiparametric estimators. Econometrica 62 (6), 1349–1382.
Pakes, A., Ostrovsky, M., Berry, S., 2007. Simple estimators for the parameters of discrete dynamic games (with entry/exit examples). RAND Journal of Economics 38 (2), 373–399.
Pan, X., Zhang, Y., Xu, L., Huang, J., Zhao, Q., 2009. An analysis of farmers' perception of the new cooperative medical system in Liaoning Province, China. BMC Health Services Research 9, 230.
Rust, J., 1987. Optimal replacement of GMC bus engines: an empirical model of Harold Zurcher. Econometrica 55 (5), 999–1033.
Sommers, B., Kronick, R., Finegold, K., Po, R., Schwartz, K., 2012. Understanding participation rates in Medicaid: implications for the affordable care act. Public Health 93, 67–74.
Sorensen, A.T., 2006. Social learning and health plan choice. RAND Journal of Economics 37 (4), 929–945.
Wagstaff, A., Lindelow, M., Jun, G., Ling, X., Qian, J., 2009. Extending health insurance to the rural population: an impact evaluation of China's new cooperative medical scheme. Journal of Health Economics 28 (1), 1–19.
Wang, H., Yip, W., Zhang, L., Hsiao, W.C., 2009. The impact of rural mutual health care on health status: evaluation of a social experiment in rural China. Health Economics 18 (S2), S65–S82.
White, H., 1982. Maximum likelihood estimation of misspecified models. Econometrica 50 (1), 1–25.
Wu, M., Zhang, Z., He, M., Ruan, Y., Lv, C., 2006. Qualitative study on the implementation and determinants of the New Cooperative Medical System in rural China. Study report from World Bank/Ministry of Health NCMS study.
Yi, H., Zhang, L., Luo, R., Liu, C., Scott, R., 2011. A survey on farmer's understanding of and benefits from New Cooperative Medical Scheme. Population Journal 1 (185), 47–53.
Yip, W., Hsiao, W., 2009. China's health care reform: a tentative assessment. China Economic Review 20 (4), 613–619.
You, X., Kobayashi, Y., 2009. The new cooperative medical scheme in China. Health Policy 91 (1), 1–9.