How China's Rural Health Program Lifted Incomes: Evidence from 800 Million Beneficiaries

Huang, Kaixing and Hou, Hao

China Center for Agricultural Policy, Peking University

8 May 2025

How China's Rural Health Program Lifted Incomes: Evidence from 800 Million Beneficiaries

Kaixing Huang **Hao Hou***

China Center for Agricultural Policy, Peking University

May 8, 2025

Abstract

This study evaluates the economic impact of the New Rural Cooperative Medical Scheme in China, the world's largest rural public health program, covering over 800 million rural residents. Using longitudinal survey data from villages that gained access to the program in different years, we find that the program improved the probability of being in good health by 4.4% to 8.2% across age groups. For the average participating household, per capita income increased by 20.3% over a decade, driven primarily by greater off-farm labor participation and higher wages, alongside significant agricultural income growth. The aggregate income gains were six times the government's program investments. These effects can be replicated by a structural model that characterizes the health investments and labor allocation of utility-maximizing rural residents. Counterfactual analyses based on the structural model suggest that China could further increase the program's benefits by raising the reimbursement rate up to 0.8 (but not beyond). Additionally, eliminating the current cross-province reimbursement constraints would further boost income gains by 18.7%.

Keywords: rural public health insurance, income, health, migration
JEL: I13, I38, R23

*Peking University. Email: Kaixing.huang@pku.edu.cn.

1 Introduction

Many developing countries provide publicly funded health programs for rural populations. Prominent examples include China's New Rural Cooperative Medical Scheme (NCMS), which insures over 800 million rural residents; India's Ayushman Bharat (PM-JAY), covering 500 million low-income individuals; and Brazil's Unified Health System (SUS), serving 75% of rural communities.[1] This study examines the impact of China's NCMS on rural income and investigates the underlying mechanisms. Understanding the magnitude and channels of this income effect is critical for China to refine its rural health policy design and for other developing countries considering the adoption or expansion of similar programs.

We focus on China's NCMS for three reasons. First, it is the world's largest public rural health insurance program. Launched in 2003, NCMS was gradually expanded across Chinese counties and by 2011 covered over 800 million rural residents, achieving an enrollment rate exceeding 96%. Second, the phased rollout of NCMS generates exogenous variation, allowing us to identify the program's causal effects. Third, we combine county-level NCMS implementation data with unique household-level longitudinal survey data from the National Fixed Point Survey (NFPS), which tracks more than 17,000 rural households annually from 2003 onward. The NFPS provides detailed information on health expenditures, health outcomes, income sources, labor allocation, and rural-urban migration. This nationally representative dataset enables us to estimate the magnitude and mechanisms of NCMS's impact on rural income and to assess the economic returns to government investments in the program.

Event-study estimates indicate that the NCMS led to a gradual increase in rural household income, with participating households experiencing an average net income growth of 20.3% over a 10-year period. These results are robust to alternative

[1] For systematic reviews of public healthcare systems in developing countries, see Pauly et al. (2006), Das and Do (2023), and Banerjee et al. (2024).

estimation methods and are not driven by pre-treatment trends, as evidenced by near-zero and statistically insignificant event-study coefficients in the pre-intervention periods. We also find that the NCMS significantly increased healthcare expenditures, though the magnitude of this increase was only about one-tenth of its effect on income growth. When combined with data on government investments in the program, these estimates suggest a 6.7-fold return over the 10-year period.

Mechanism analysis suggests that household income growth is primarily driven by off-farm income growth, attributable to health improvements resulting from the NCMS. We find that the NCMS increased the likelihood of being healthy by 4.2% to 7.8% across different age groups. For the working-age population, the NCMS raised the probability of engaging in off-farm work by 5.1% over a 10-year period and increased average off-farm working time by nearly one month. Beyond labor participation, the NCMS also significantly enhanced rural residents' labor productivity in off-farm work, as measured by off-farm wages. Additionally, we observe a positive and statistically significant impact of the NCMS on agricultural income, driven by higher per-labor agricultural output. However, the magnitude of this effect is only one-fourth as large as its impact on off-farm income.

We also find that NCMS affected the migration pattern of rural residents: the likelihood of engaging in off-farm work outside the home province (as opposed to off-farm work within the home province) is increased by 10.3% over a 10-year period. As the average off-farm wage within home province is significantly lower than that outside home province, this effect on migration pattern suggests an inefficiency of labor allocation created by the program. This finding is unsurprising, as the NCMS was originally designed as a local scheme that only permits reimbursement for medical services in individuals' registered provinces. While substantial efforts have been made to streamline cross-province reimbursement, individuals using off-province medical services still face much lower reimbursement rates even when cross-province reimbursement is feasible (Refer to Subsection 2.2 for details).

We develop a structural model to verify the impact of NCMS on income and to investigate possible improvements in the program design. The model characterizes the labor allocation and health investments of utility-maximizing rural residents and allows health to affect labor productivity and utility. Estimated based on NFPS data and exogenous health shocks from NCMS, the model is able to replicate the empirically estimated effect on health, labor allocation, migration pattern, and income. Counterfactual analysis based on the structural model suggests that the income gains from the program increases with the reimbursement rate up to 0.8 and declines after that. More importantly, we find that eliminating the cross-province reimbursement constraints would increase the income gains for all range of reimbursement rates and could further boost income gains by 18.7% at the optimal reimbursement rate.

Numerous studies have examined the effects of China's NCMS on healthcare utilization (Lei and Lin, 2009), health outcomes (Cheng et al., 2015), mortality (Chen and Jin, 2012; Gruber et al., 2023), adolescent outcomes (Huang and Liu, 2023), out-of-pocket healthcare payments (Wagstaff et al., 2009; Babiarz et al., 2010), health shock-related outcomes (Liu, 2016), rural entrepreneurship (Wang et al., 2024; Liu and Zhang, 2018), and household savings and consumption (Bai and Wu, 2014; Cheung and Padieu, 2015; Chen et al., 2022). Most of these studies report positive effects of the NCMS. Similarly, several studies have explored the impact of rural public health insurance in other developing countries. For example, Raza et al. (2016) examined the impact of community-based health insurance on healthcare access and the financial consequences of illness in rural India, Garcia-Mandicó et al. (2021) estimated the effect of public health insurance on out-of-pocket medical payments and consumption in Ghana, and Neelsen et al. (2019) assessed the effect of universal health coverage on economically vulnerable populations in Thailand.

Distinct from existing studies, this paper focuses on estimating the impact of the program on rural household income using the unique NFPS data. Our estimates enable us to calculate the economic return on public investments in the program, which has significant policy implications for developing countries considering the adoption or expansion of rural health programs. Likely due to the limited availability of large-scale panel data linking rural household income with public health insurance enrollment, only a few existing studies have estimated the effect of rural public health insurance on rural income using randomized experiment data. For instance, based on randomized experiments with 789 informal workers in Kenya, Haushofer et al. (2020) found that free health insurance had no significant effect on income; based on experimental data from 516 farmers in Zambia, Fink and Masiye (2015) found that subsidized investments in preventive healthcare increased agricultural output by 14.7%. To the best of our knowledge, our study is the first to estimate the effect of a national rural public health insurance program on income using nationally representative microdata.

This paper also contributes to understanding the mechanisms through which rural public health programs affect income. On the one hand, health improvements resulting from public health insurance could increase labor market access and labor supply for individuals (Bartel and Taubman, 1979; Hokayem and Ziliak, 2014) and their family members (Blau et al., 1996; Fadlon and Nielsen, 2021). On the other hand, many studies find that access to public health insurance reduces employment through the mechanism of ”employment lock”—where workers remain employed primarily to secure private health insurance coverage (e.g., Garthwaite et al., 2014; Boyle and Lahey, 2010). However, nearly all these studies are based on data from urban employers in developed countries. The mechanisms of the income impact could be different and more complex for rural public health programs in developing countries, where family-based agricultural production is prevalent. Our study reveals that China’s NCMS influences rural income by affecting off-farm work participation, labor productivity in both agricultural and non-agricultural sectors, and migration patterns.

Finally, this paper contributes to understanding the efficiency of the current NCMS design and proposing potential improvements. Although we find that NCMS has significantly increased rural income, we also show that further income gains can be obtained by adjusting the current program design. Based on a structural model featuring the NCMS policy design, we find a nonlinear association between the reimbursement rate and household income, with a turning point higher than the current real reimbursement rate. This finding suggests potential welfare gains from increasing the reimbursement rate. More importantly, the structural model suggests that eliminating the current cross-province reimbursement constraints could substantially increase the program's benefits under any reimbursement rate. These findings have important policy implications not only for China but also for other developing countries hoping to adopt or refine similar programs.

The remainder of this paper is organized as follows. Section 2 provides background on China's rural public health system and details the features of the NCMS. Section 3 presents the data and empirical strategies. Section 4 reports the empirical results. Section 5 introduces the structural model and provides counterfactual analysis. Section 6 concludes. Additional results are provided in the Online Appendix.

2 Background

2.1 Rural Medical System in China

Since the founding of the People's Republic of China in 1949, the government has actively promoted cooperative medical services as part of its rural healthcare strategy. In the 1950s, China encouraged agricultural cooperatives to establish grassroots health stations through collective financing, laying the foundation for a decentralized but functional rural healthcare network. Over the next four decades, this system expanded, providing basic medical services to millions of rural residents.

However, the introduction of the Household Responsibility System in the early 1980s led to the decline of collective farming and the weakening of rural cooperatives. As the collective economy disintegrated, so too did its financial support for cooperative medical services. Poor management and insufficient oversight further accelerated the system's collapse, leaving rural China with virtually no healthcare coverage by the 1990s. By 1990, fewer than 10% of rural households had health insurance (Wagstaff and Lindelow, 2008). By 2002, just before the launch of the NCMS, coverage had plummeted to around 4% (You and Kobayashi, 2009). This healthcare vacuum underscored the urgent need for reform, paving the way for the NCMS in 2003, which sought to rebuild rural medical security.

During the NCMS era (2003–2015), medical insurance funds were managed at the county level, and reimbursement scopes and rates differed from those of urban residents' policies. In January 2016, the Urban Resident Basic Medical Insurance and the NCMS were merged, establishing a unified Urban and Rural Resident Medical Insurance System. After the reform, rural and urban residents enjoyed identical reimbursement coverage and rates.

2.2 The New Rural Cooperative Medical Scheme

The NCMS was piloted in 2003 as part of China's efforts to rebuild rural healthcare following the collapse of the pre-1980s cooperative system. In October 2002, the Chinese government explicitly proposed the gradual establishment of a new rural cooperative medical system nationwide. It required local governments to conduct pilot programs first, summarize experiences, and gradually expand coverage, with the goal of covering the rural population by 2010. Starting in 2003, local governments began piloting the NCMS. The selection of pilot counties was somewhat random nationwide, but counties with larger agricultural populations and higher poverty rates were often prioritized. By 2004, 310 counties across 30 provinces had launched

NCMS pilots, covering 95.04 million rural residents, with 68.99 million rural residents actually participating. By 2006, pilot counties accounted for about 40% of all counties nationwide; this expanded to 60% in 2007, achieved nationwide implementation by 2008, and reached 832 million participants by 2011, with an enrollment rate exceeding 96%, making it the world's largest rural health insurance program by far.

The NCMS was a government-organized, guided, and supported voluntary medical mutual aid system for rural residents, funded by individuals, collectives, and the government, primarily focusing on major illness coverage. Participating rural residents, on a household basis, paid an annual premium per person to township fiscal offices or health centers, which were then transferred to county finance bureaus and deposited into dedicated NCMS fund accounts. These funds, combined with government subsidies, formed the pooled NCMS fund, managed by state-owned banks or rural credit cooperatives designated by county-level NCMS management committees. Rural residents could directly claim partial medical expenses at designated county-level healthcare facilities, subject to annual caps. Initially, the policy required beneficiaries to contribute 10 yuan per person, matched by a 10-yuan government subsidy. Contributions increased significantly after 2008, with government subsidies rising to 80 yuan per person in 2009, 240 yuan in 2012, and 380 yuan in 2015. Figure 1 shows the annual government and individual contributions to NCMS.

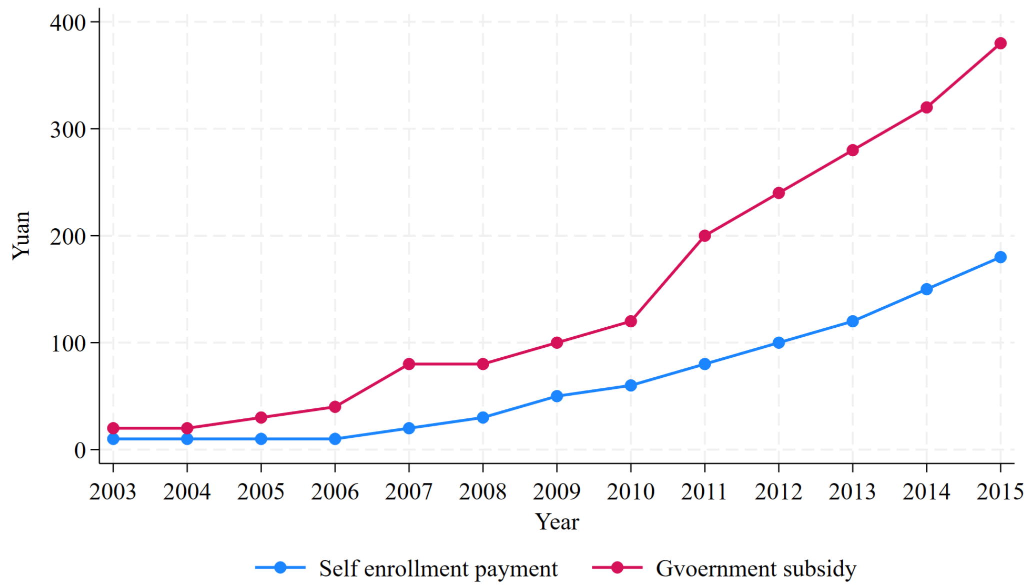

Figure 1: Government subsidies and individual enrollment payments in the NCMS
Notes: The data are sourced from news reports and official documents published annually on the official website of China's National Health Commission (http://www.nhc.gov.cn/).

In the early pilot phase, NCMS inpatient reimbursement rates were typically set at 30%–50%, gradually increasing over time. For example, the average rate was 38.2% in 2007, 49.1% in 2009, and about 70%–75% by 2015. Outpatient reimbursement rates remained lower, typically 30%–50% even in 2015. After the merger of NCMS with the Urban Resident Basic Medical Insurance in 2016, rural and urban residents received identical reimbursement coverage and rates. However, actual reimbursement was constrained by caps, deductibles, and non-covered drugs, often leaving out-of-pocket costs higher than the theoretical rates. In addition, reimbursement varied by hospital tier, regional policies, and treatment types. For instance, in 2024, inpatient rates were 85%–95% in township/primary hospitals, 70%–85% in county/secondary hospitals, and 50%–70% in provincial/tertiary hospitals. Outpatient rates were much lower in the same year: 60%–80% in township/primary hospitals, 50%–70% in county/secondary hospitals, and 40%–60% in provincial/tertiary hospitals.

Initially designed as a local (county-level) scheme, NCMS faced challenges with cross-region reimbursement. During 2003–2010, reimbursement followed a jurisdictional management principle, meaning participants could only claim expenses at designated facilities in their registered residence, with cross-province claims largely unavailable. In 2011, cross-province verification mechanisms were explored, but the norm remained "pay first, claim later at home." By 2013, intra-province networks were piloted, with Guangdong and Jiangsu establishing provincial platforms for real-time settlement. In 2017, a national platform enabled direct cross-province inpatient settlement for NCMS enrollees via a filing system. However, by 2020, only 60% of cross-province inpatient claims were settled directly, and outpatient claims remained mostly intra-province. In 2021, cross-province outpatient pilot coverage expanded to regions like Beijing-Tianjin-Hebei and the Yangtze River Delta, including chronic disease claims. However, actual reimbursement rates were lower due to higher deductibles (e.g., tertiary hospital standards) and regional formulary gaps, reducing reimbursement by 10%–15% compared to local rates. Outpatient coverage remained limited, with only 30% of regions enabling cross-province claims.[2]

---

[2]The data in this subsection were collected from various government reports, statistical yearbooks, and news reports:

(a) *Opinions on Establishing a New Rural Cooperative Medical System* (State Council Document No. 3 [2003]) `https://www.gov.cn/`

(b) *Guidelines on Verifying and Reimbursing Cross-Province Medical Expenses Under the New Rural Cooperative Medical System* (Document No. 27 [2011] by the Ministry of Health and Ministry of Agriculture) `http://www.nhc.gov.cn/`

(c) *Notice on Accelerating the Integration of Basic Medical Insurance Systems for Urban and Rural Residents* (State Council Document No. 3 [2016]) `https://www.gov.cn/zhengce`

(d) *Administrative Measures for Direct Settlement of Cross-Province Inpatient Medical Expenses* (Ministry of Human Resources and Social Security Document No. 10 [2017]) `https://www.mohrss.gov.cn/`

(e) *China Health Statistics Yearbook* (2003–2020)

(f) *National Healthcare Security Development Statistical Bulletin* (National Healthcare Security Administration, 2018–2024)

(g) *New Rural Cooperative Medical System Expands Cross-Province Reimbursement to 9 Provinces* (People's Daily, 2017) `http://www.people.com.cn/`

(h) *Medical Insurance Cross-Region Settlement: From "Traveling for Reimbursement" to "Direct Card Payment"* (Xinhua News Agency, 2023) `https://www.news.cn/`

3 Data and Method

3.1 Data

3.1.1 National Fixed Point Survey

Our analysis relies on data from the National Fixed Point Survey (NFPS), a longitudinal survey conducted by the Research Center of Rural Economy in China. The NFPS villages were selected for representativeness based on various factors, including region, income, cropping pattern, population, and non-farm activities. Within each village, a random sample of households was selected, typically ranging from 50 to 100 households, depending on the village size. If a sample household permanently relocated, it was replaced by a randomly selected new household within the same village, which was assigned a new household ID. The dataset constitutes an unbalanced panel, with 91.2% of the sample households having data for at least five years. The NFPS data includes more than 18,000 households per year from approximately 347 villages. The NFPS data has been demonstrated to be of high quality (DeBrauw et al., 2002; Benjamin et al., 2005) and has been widely employed in the literature (Kinnan et al., 2018; Chari et al., 2021; Huang et al., 2024; Huang and You, 2025).

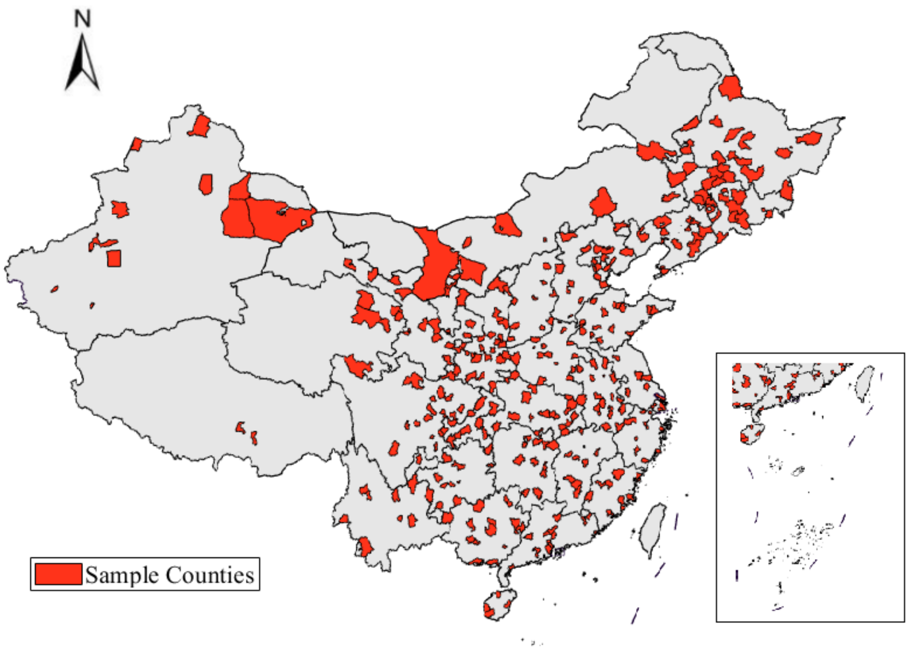

Figure 2: Map of the NFPS sample

Notes: Our sample consists of 313 villages from the NFPS, which are located within 313 counties (highlighted in red) distributed across all provinces in mainland China.

Our main analysis uses NFPS data from annual survey waves between 2003 and 2015 for 313 villages. Key variables in our analysis, such as individual labor allocation, are only available starting from the 2003 wave, and data after 2015 are not accessible to us. We exclude 34 NFPS villages that could not be matched to county IDs due to administrative division adjustments of villages or counties, which is necessary for merging with the policy data. Additionally, we exclude sample households that were present for fewer than five years during 2003–2015. The final dataset includes an average of 17,877 households per year. Our main analysis focuses on adults (aged 16 and above) from these rural households. Figure 2 shows the counties where the sample villages are located. Note that the NFPS typically surveys only one village per county.

The NFPS data is particularly suitable for our analysis for several reasons. First, its national coverage ensures representativeness for Chinese villages. Second, the longitudinal nature of the survey, spanning a long period, allows us to identify policy effects using a difference-in-differences approach. Finally, and most importantly, the survey provides detailed individual- and household-level data on our key variables of interest, including health status, medical expenditures, net income, and labor allocation.

3.1.2 Roll out of NCMS across counties

We collect data on the starting year of the NCMS for each sample county from local government websites. The NCMS information is typically published on the websites of the prefectural-level city or the province to which the county belongs. For sample counties where NCMS information is unavailable on official websites, we search online reports and news articles to identify the policy's starting year. Figure 3 illustrates the rollout of the NCMS across our sample counties. Since each sample county generally contains only one sample village, the figure also represents the policy's rollout across NFPS villages. The figure shows that NCMS adoption began in 2003, progressed rapidly, and was implemented in almost all sample counties by 2007. By 2015, 96% of our sample villages had enrolled in the NCMS, while the remaining 4% (13 villages) had not.

Figure 3: Rollout of NCMS across NFPS villages

Notes: The village-level rollout data for NCMS adoption were collected by the authors from various public reports published by central and local governments.

3.1.3 Summary statistics

Table 1 summarizes the key variables used in this study. Panel A presents household-year level variables. The average annual net income per household is 29,706 yuan. Households earn an average annual agricultural income of 6,873 yuan, accounting for 26.2% of their total net income. On average, households allocate 187 labor days per year to agricultural work. Panel B presents individual-year level data for adults within each household. The average adult spends 108 days per year on off-farm work, earning an annual off-farm income of 3,824 yuan. Among adults engaged in off-farm work, 74.4% work within their home province, while the remaining 25.6% work outside their province.

Following standard classifications in health assessments, public health studies, and occupational health evaluations, the survey categorizes individual health status into five levels: 1. Excellent (5): Very good health with no significant medical issues; 2. Good (4): Generally healthy, possibly with minor or well-managed conditions; 3.

Moderate (3): Noticeable health problems requiring regular medical attention; 4. Poor (2): Significant health issues frequently interfering with daily life; 5. Unable to work (1): Severe health conditions preventing employment or independent living. Higher numerical values indicate better health status (5 = best, 1 = worst). The average health index value for adults is 4.28.

Table 1: Summary Statistics

Variable	N	Mean	SD
Panel A. Household-year level			
Net income (Yuan)	207,653	29,706	25,991
Agricultural income (Yuan)	207,573	6,783	10,893
Family size	207,652	3.88	1.60
Agricultural labor days	182,891	187	218
Panel B. Individual-year level			
Off farm work days	673,070	108	134
Off-farm net income (Yuan)	673,070	3,826	13,224
Health status[a]	805,980	4.28	0.99
Off-farm work location[b]	324,859	0.26	0.44
Age	673,070	43.95	16.85
Years of schooling	673,070	6.85	3.46
Gender (male=1; female=0)	673,070	0.52	0.50

Notes: All monetary values are expressed in constant 2010 yuan. Data on agricultural labor days are reported at the household level, whereas off-farm work days are measured at the individual level. The sample size for agricultural labor days is smaller due to missing values. [a]Health status is a categorical variable defined as follows: 5 = excellent, 4 = good, 3 = moderate, 2 = poor, and 1 = unable to work. [b]Off-farm work location is a binary variable, where 1 indicates work outside the home province and 0 indicates work within the home province; observations without off-farm work are excluded from this measure.

Figure 4 provides suggestive evidence of a positive effect of the NCMS on health outcomes during the period 2003–2015. Panel A displays the distribution of health status among the working-age population (ages 16–60), categorized as follows: *Good health*—individuals with a health index score of 5 (excellent); *Moderate health*—individuals with scores of 4 (good) or 3 (moderate); *Poor health*—individuals with scores of 2 (poor) or 1 (unable to work). From 2003 to 2015, we observe an increasing trend in the share of the population reporting good health, a declining trend in the share reporting moderate health, and no significant trend in the share reporting poor health. Panel B illustrates the quadratic relationship between age and the health index in 2003 and 2015. The results indicate that health status first increases and then declines with age. Notably, the curve shifts upward from 2003 to 2015, suggesting improved health outcomes across most adult age groups during this period.

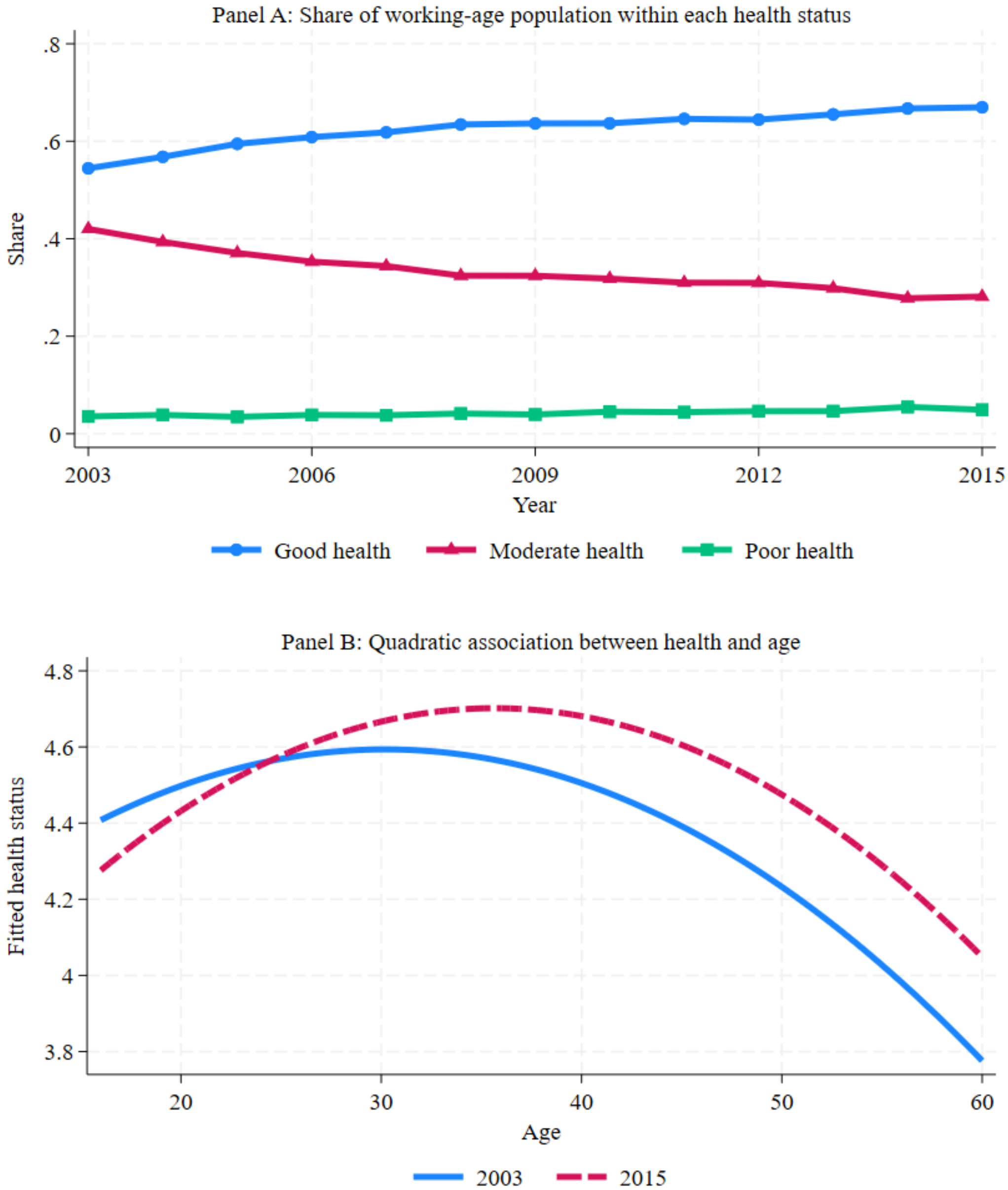

Figure 4: Changes in health over time

Notes: Panel A displays the distribution of health status among the working-age population (ages 16–60), categorized as follows: *Good health*—individuals with a health index score of 5 (excellent); *Moderate health*—individuals with scores of 4 (good) or 3 (moderate); *Poor health*—individuals with scores of 2 (poor) or 1 (unable to work). Panel B illustrates the quadratic relationship between age and the health index in 2003 and 2015.

3.2 Method

Our empirical strategy relies on the exogeneity of the NCMS rollout across our sample villages. Recall that the policy rollout occurs at the county level. Since each county in our sample contains only one sample village, the policy rollout can be interpreted at the village level. The policy effect is estimated by comparing villages that adopted NCMS early with those that adopted it later (or never during our sample period). The identification assumption is that villages subject to NCMS early and later would exhibit no differential trends in the outcome variables of interest in the absence of the policy. Many existing studies on China's NCMS have adopted a similar identification strategy (e.g., Gruber et al., 2023; Huang and Liu, 2023; Wang et al., 2024), though they focus on different issues and use different datasets. To validate this assumption, we control for individual- (or household-) and year-fixed effects alongside other control variables. Additionally, we conduct a falsification test to provide supporting evidence for the identification assumption.

Specifically, we estimate the effect of NCMS using the following event-study regression model:

$$y_{ivt} = \sum_{k=-J,k\neq-1}^{k=J} \beta_k NCMS_{v,t+k} + \theta_i + \theta_t + X_{ivt}\beta + \epsilon_{ivt} \ , \tag{1}$$

where y_{ivt} represents the outcome variable for individual (or household) i in village v during year t. The primary outcomes of interest include individual health status, household net income, and labor allocation. The key explanatory variable, $NCMS_{v,t+k}$, is a dummy variable indicating whether year t is k years relative to the NCMS implementation year in village v.

The model incorporates individual-fixed effects (or household-fixed effects) θ_i to account for time-invariant individual (or household) characteristics, as well as year-fixed effects θ_t to capture common annual shocks across all households. To address potential preexisting trends, the model controls for the initial values of the household's primary income source and the individual's main work industry. These two variables are interacted with a full set of year dummies to account for their time-invariant effects. Additionally, we include province-specific time trends to flexibly control for other time-varying factors. These control variables are included in the vector X_{ivt}. To avoid over-control bias, we do not control for other time-varying variables that may themselves be influenced by NCMS (and thus act as channel variables). Standard errors are clustered at the village level. The estimation focuses primarily on adults (aged 16 and above) from the 17,877 rural households observed between 2003 and 2015.

The coefficients of interest, β_k ($k \geq 0$), capture the effect of the policy on the outcome variable. The coefficients β_k ($k < 0$) serve as a placebo or falsification test. If the estimated policy effect is not driven by preexisting differences between villages that adopted NCMS earlier versus later, we expect the estimates of β_k ($k < 0$) to be close to zero and statistically insignificant. Note that $k = -1$ serves as the base year and is omitted from the regression. Our baseline analysis estimates model (1) using ordinary least squares. To assess the robustness of the event-study estimates to heterogeneous treatment effects, we also employ the estimation methods proposed by Borusyak et al. (2024), Sun and Abraham (2021), and Callaway and Sant’Anna (2021).

4 Empirical results

4.1 Effect on income

Panel A of Figure 5 presents the dynamic effects of NCMS on household net annual income. The estimates suggest a significantly positive effect that increases over time. For the average household, NCMS increased household net income by 8,885 yuan over a 10-year period, with an average annual effect of $4,371$ yuan. The growth in the effect over time is plausibly attributable to the accumulated health benefits of the program and the gradual increase in NCMS reimbursement rates over the years. The estimated effect is non-trivial: given that the average annual household income by the end of our sample period was 44,151 yuan, the results imply that NCMS raised annual income by approximately 20.1% after a decade of implementation.

Panel B presents the estimated effect of NCMS on household medical expenditures (before reimbursement). We focus on household-level medical expenditures because the survey does not collect medical expenditure data at the individual level. The estimates indicate that the policy increased annual pre-reimbursement medical expenditures by 1,236 yuan over a 10-year period. Since this effect is substantially smaller than the income effect shown in Panel A (only 13.7% of the income gain), we conclude that NCMS led to a significant increase in real household income. This comparison is essential because medical expenditures (and other consumption) are not excluded from the calculation of household net income. The observed rise in medical expenditures further confirms that NCMS significantly increased the utilization of medical services.

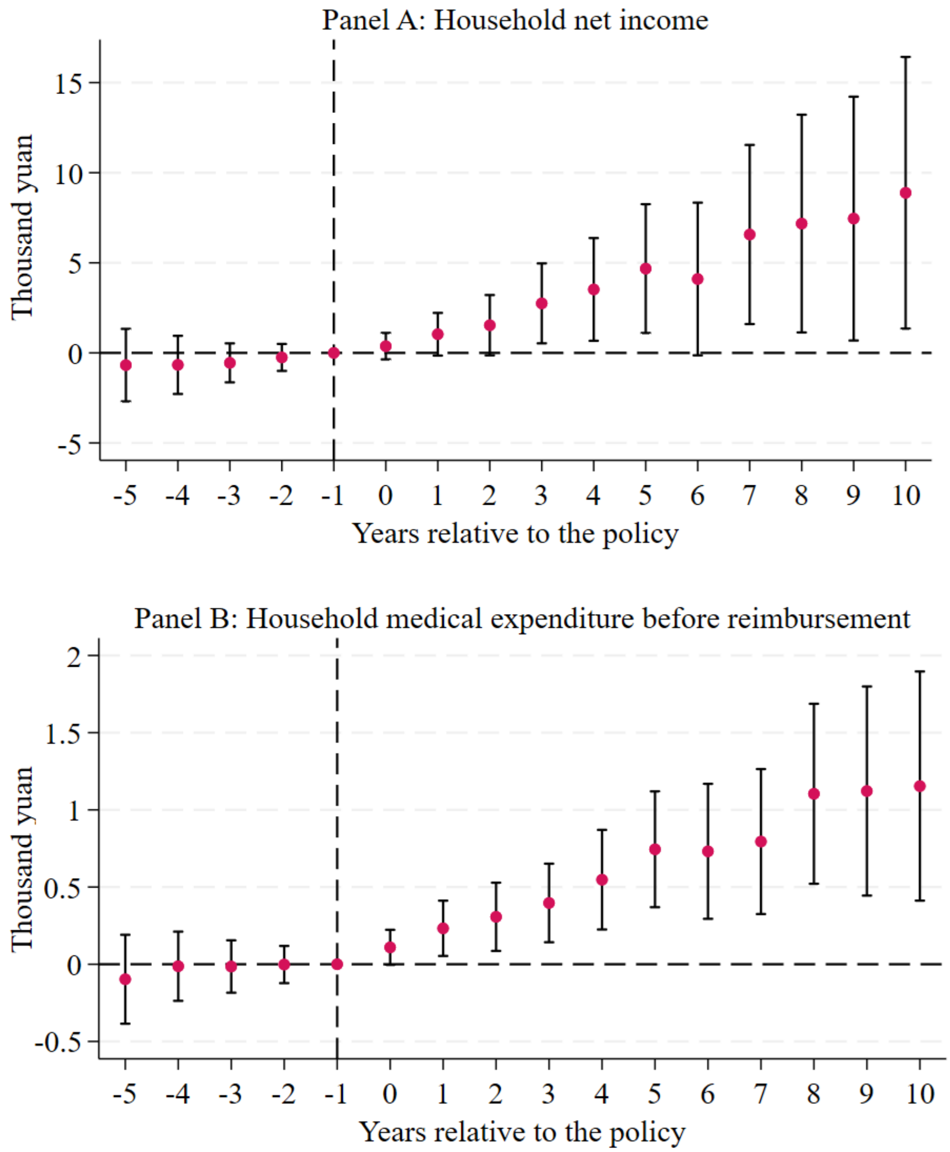

Figure 5: Effects of NCMS on household net annual income and medical expenditure

Notes: This figure presents the effects of NCMS on household net annual income (Panel A) and household medical expenditures before reimbursement (Panel B), estimated based on model (1) using different dependent variables. The capped spikes represent 95% confidence intervals, computed using standard errors clustered at the village level.

Figure 6 demonstrates that the income effect is primarily driven by growth in off-farm income. Panel A displays the effect on household net off-farm income, while Panel B shows the effect on household net agricultural income. Off-farm income includes net earnings from off-farm wage employment and self-employed non-agricultural activities, whereas agricultural income consists of household net income from crop production. Although we observe significantly positive and increasing effects on both off-farm and agricultural incomes, the effect on off-farm income is substantially larger. Specifically, over a 10-year period, the policy increased household off-farm income by 5,810 yuan, compared to only 1,532 yuan for agricultural income. We will later explore the mechanisms behind these sectoral differences.

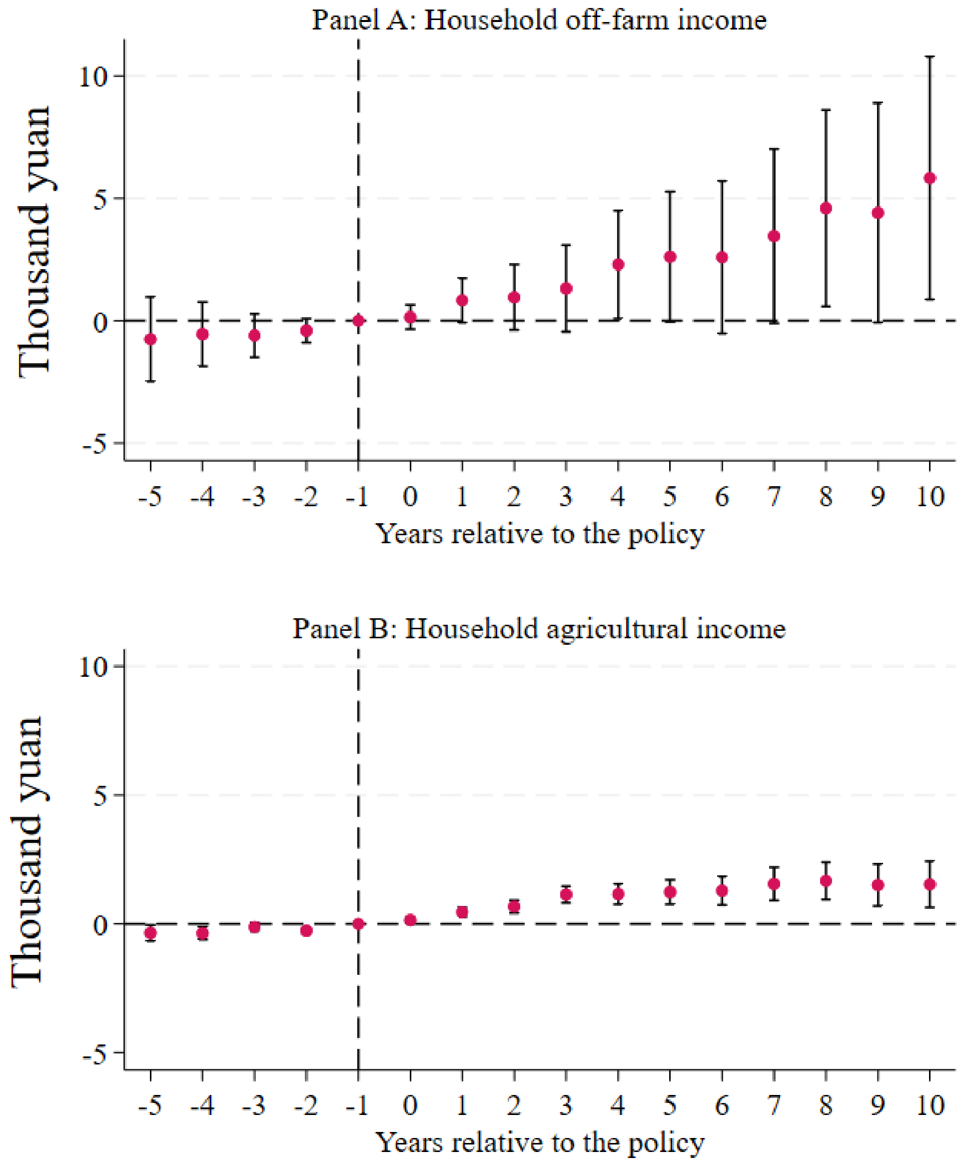

Figure 6: Effects of NCMS on household off-farm income and agricultural income

Notes: This figure presents the dynamic effects of NCMS on household off-farm income (Panel A) and agricultural income (Panel B), estimated using model (1). Off-farm income includes net earnings from off-farm wage employment and self-employed non-agricultural activities, while agricultural income comprises household net income from crop production. The capped spikes indicate 95% confidence intervals.

4.2 Robustness checks and heterogeneity

Figure 7 examines the robustness of the baseline income effect estimates to subsamples and potential confounding factors. First, we restrict the sample to households that have at least 3 periods before treatment and 5 periods after treatment to address concerns about using an unbalanced panel dataset. Second, we exclude households from the richest 10% and poorest 10% villages to mitigate potential bias from extreme values. Third, we control for county-level GDP per capita to account for differences in local off-farm employment opportunities. Finally, we control for variations in the timing of *Hukou* system reform across prefectural cities to which the villages belong, thereby excluding potential confounding effects from the relaxation of migration constraints.[3] All resulting estimates remain comparable to the baseline estimates.

[3] The Hukou system is China's household registration system, which serves as a domestic passport determining citizens' access to public services based on their registered location. We collected data on the timing of the gradual relaxation of Hukou restrictions in each prefectural city from local government websites.

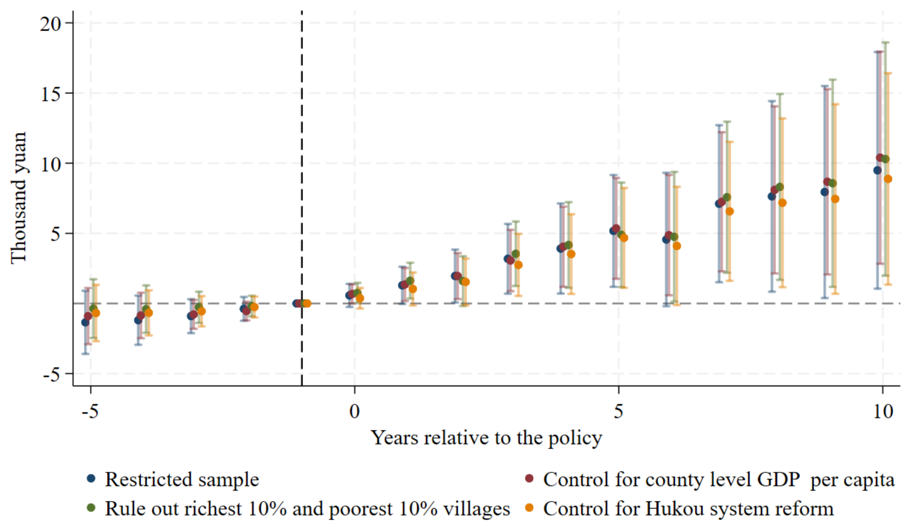

Figure 7: Robust to sub-samples and potential confounding factors

Notes: This figure presents robustness checks of the estimated effect on household net income. Panel A restricts the sample to households with at least 3 pre-treatment periods and 5 post-treatment periods. Panel B excludes households from the richest 10% and poorest 10% villages. Panel C controls for county-level GDP per capita. Panel D controls for variation in the timing of *Hukou* system reforms across the prefectural cities to which the villages belong. The capped spikes represent 95% confidence intervals.

Various other robustness checks are presented in Figure 8 and Appendix Figures A1 and A2. Figure 8 adopts three alternative estimation methods proposed by Borusyak et al. (2024), Sun and Abraham (2021), and Callaway and Sant' Anna (2021) to assess the robustness of the event-study estimates to heterogeneous treatment effects. The resulting estimates are generally smaller but show no statistically significant difference from the baseline estimates. Appendix Figure A1 estimates a version of model (1) that uses net income per capita as the dependent variable; we do not adopt this measure due to concerns that family size (determined by fertility, mortality, and marriage) could be endogenous. The resulting estimates are comparable when multiplied by the average family size. Appendix Figure A2 presents placebo tests. We randomly reassign the timing of NCMS coverage across villages 100 times and re-estimate equation (1) for each permutation. The resulting counterfactual estimates are close to zero and statistically insignificant.

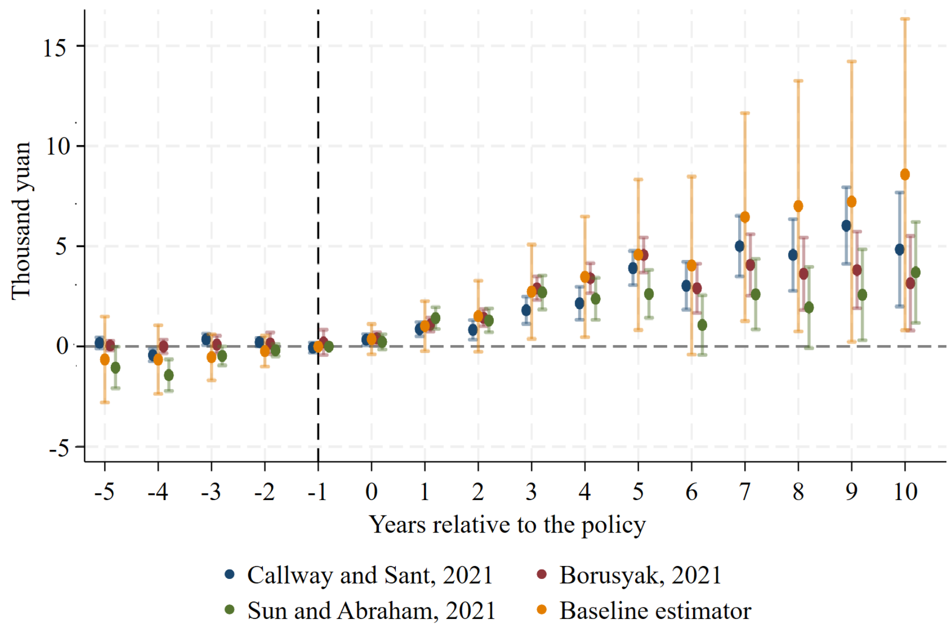

Figure 8: Robust to heterogeneous treatment effects

Notes: This figure displays robustness checks of the effect on household income with respect to heterogeneous treatment effects, using methods proposed by Borusyak et al. (2024), Sun and Abraham (2021), and (Callaway and Sant' Anna, 2021), respectively. The capped spikes represent the 95% confidence intervals.

Appendix Figure A3 examines the heterogeneity of income effects with respect to initial household income level, health status, and dependency ratio. We analyze heterogeneity based on the initial values of these variables, as they are potentially endogenous. For initial income level and dependency ratio, we classify the sample into two groups based on their median values. For initial health status, we classify the sample based on whether the household contained unhealthy individuals. The results show no significant differences in effects between these subgroups. The comparable effects for households with and without unhealthy members suggest that the program benefits not only families with existing health problems. This pattern may occur because health status changes over time, meaning the program could also benefit initially healthy individuals who may develop health issues later.

4.3 Mechanisms of the income effect

This section demonstrates that NCMS affects income through improving health outcomes, increasing off-farm labor participation, enhancing productivity in both off-farm and agricultural work, and reshaping rural residents' migration patterns.

4.3.1 Health

Figure 9 presents the dynamic effects of NCMS on health outcomes, estimated using model (1). The dependent variable is a binary health indicator constructed from self-reported health status (5 = excellent, 4 = good, 3 = moderate, 2 = poor, and 1 = unable to work), where values 5–3 are coded as 1 (healthy) and 2–1 as 0 (unhealthy). The analysis examines three age groups: young adults (16–45), middle-aged (45–60), and seniors (above 60). Results indicate that NCMS significantly increased the probability of being in good health for all age groups, with effects growing over time. The point estimates show a modest age gradient (though statistically insignificant), ranging from 4.4% to 8.2% across groups, with a mean effect of 6% over the 10-year observation period.

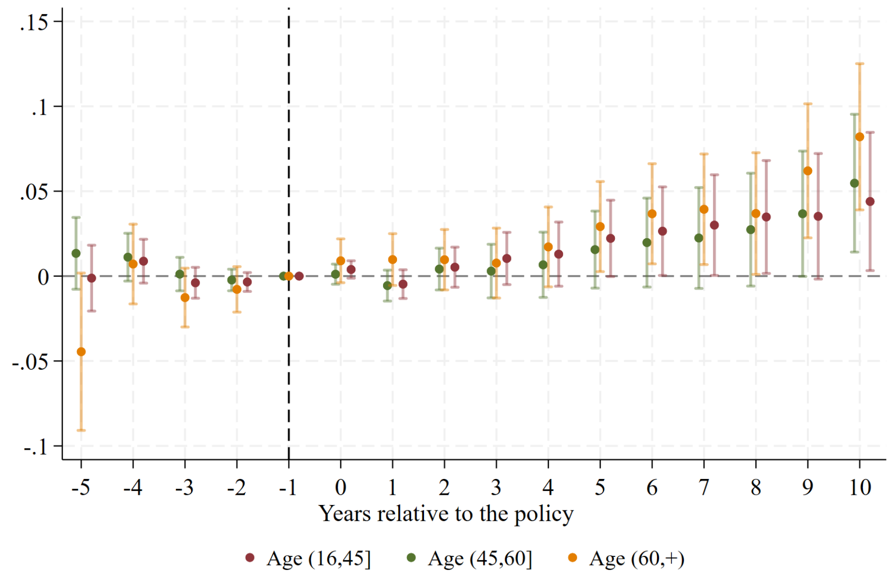

Figure 9: Effect of NCMS on health

Notes: This figure presents the estimated effect of NCMS on individuals' health outcomes using model (1). The dependent variable is a binary health indicator (1 = healthy; 0 = unhealthy). We estimate separate effects for three adult age groups, with capped spikes representing the 95% confidence intervals.

4.3.2 Off-farm employment

Figure 10 presents the effects of NCMS on off-farm employment. We find that NCMS increased the probability of off-farm work participation by 5.3% for the average adult (Panel A) and raised annual off-farm working time by 27 days over a 10-year period. These estimates align with the finding that NCMS primarily increased off-farm income (Panel A of Figure 6), suggesting that health status is a crucial determinant of rural residents' off-farm income growth. This relationship emerges because: (1) illness directly constrains individuals' off-farm work opportunities and working time, and (2) sick family members requiring care may indirectly limit healthy members' off-farm labor supply.[4] This finding aligns with the summary statistics presented in

[4]We exclude agricultural working time from our estimation for three reasons: First, precise measurement is challenging as most Chinese rural residents engage in agriculture part-time. Second, aggregating working hours across individuals of varying ages and health status may yield misleading results. Third, given the small estimated effect on agricultural income (Panel B of Figure 6), any impact on agricultural working time is likely small.

Appendix A4, which show that individuals with poor health have a 43.18% lower probability of engaging in off-farm work compared to those in good health and moderate health.

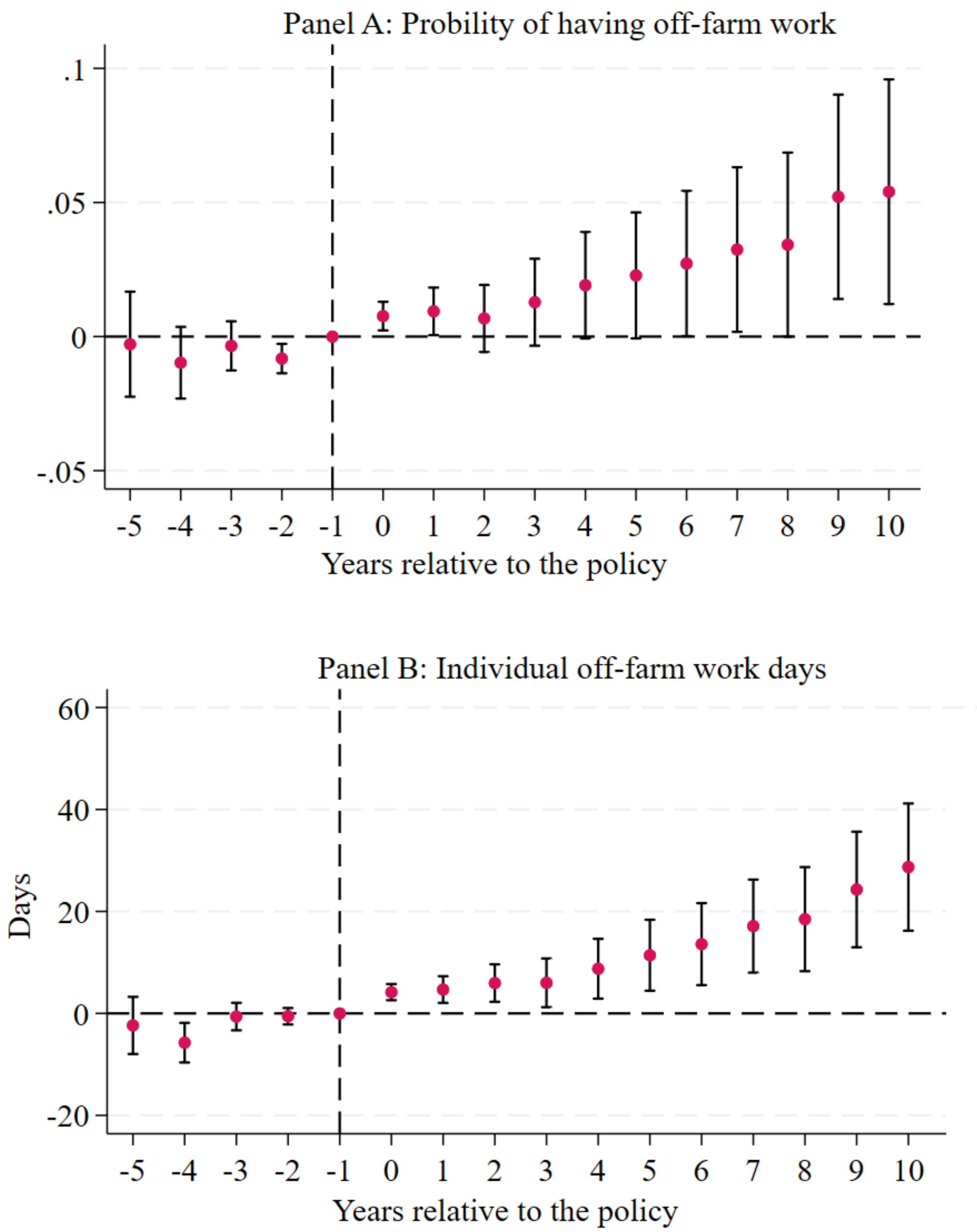

Figure 10: Effect of NCMS on off-farm employment

Notes: This figure displays the estimated effects of NCMS on two labor market outcomes for adults: (1) the probability of off-farm employment (Panel A) and (2) annual off-farm working days (Panel B). Estimates are derived from the individual-level specification of model (1), with capped spikes indicating 95% confidence intervals.

4.3.3 Labor productivity

Figure 11 shows that NCMS also increases labor productivity, measured by off-farm wages and per capita agricultural output. We find that NCMS increased off-farm wages by 20 yuan per day (about $3 USD) and increased per-labor agricultural output by 59 yuan (about $8 USD) over a 10-year period. Note that the effect on agricultural labor productivity should be interpreted with caution for two reasons. First, as we do not have a precise measure of agricultural labor (see Footnote 4), we roughly estimate agricultural labor by counting family members involved in agricultural production. Second, the increase in per-labor agricultural output may simply result from reduced labor input for a given farmland area.

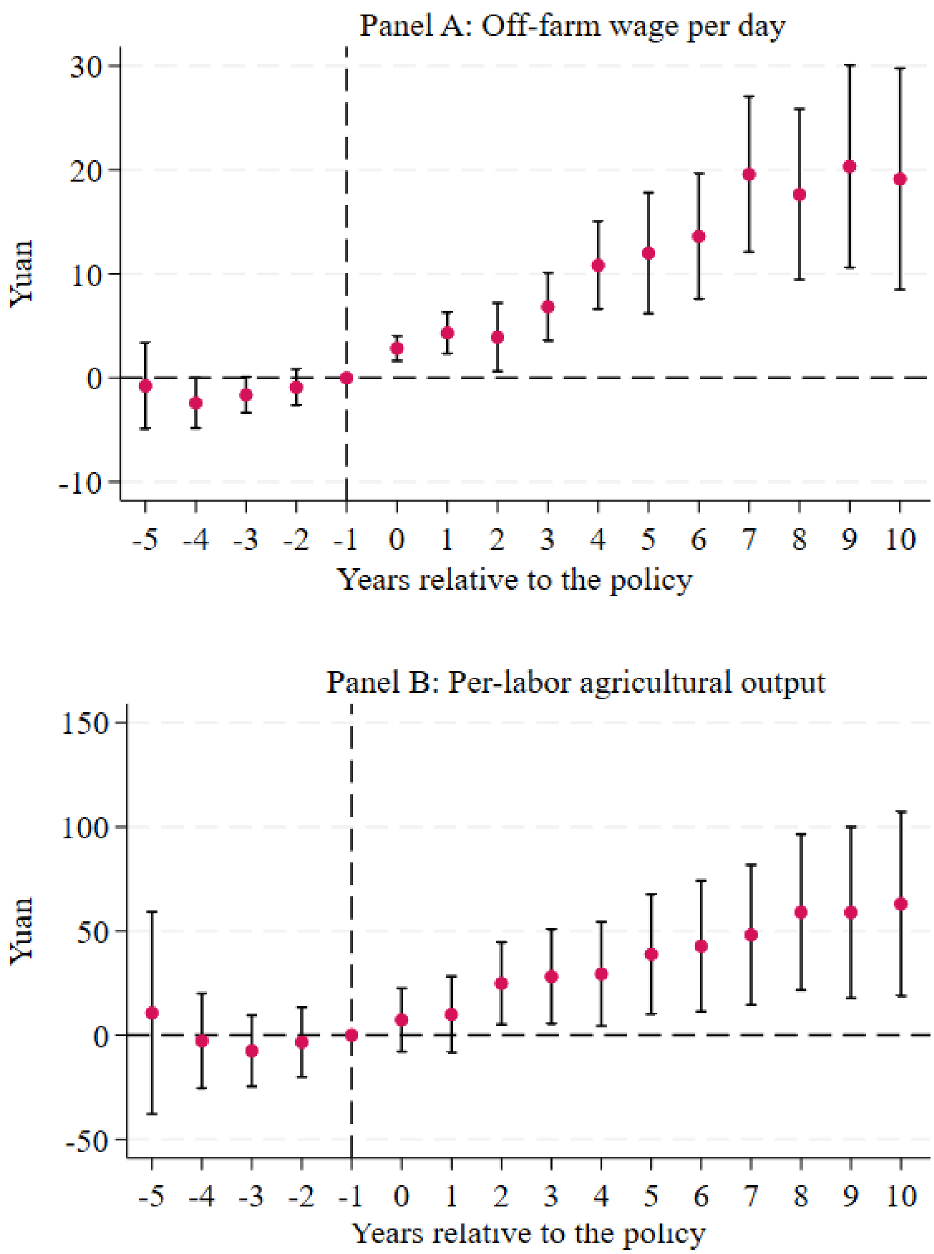

Figure 11: Effect of NCMS on labor productivity

Notes: This figure presents the effects of NCMS on labor productivity in off-farm work (Panel A) and agricultural work (Panel B), estimated using model (1). The capped spikes present the 95% confidence interval.

4.3.4 Migration pattern

Figure 12 shows that NCMS has a significant effect on the migration patterns of rural labor. We find that NCMS reduces the probability of having off-farm work outside the home province (relative to inside the home province) by 10.3% over a 10-year period.[5] This finding is consistent with the fact that, as detailed in Section 2, NCMS initially only allowed reimbursement for medical expenditures within the province where the rural residents were registered. Even after policy reforms since 2010, cross-province reimbursement still faces issues such as cumbersome procedures and low reimbursement rates. This policy design could motivate rural migrants to choose a working location within their home province.

This finding has important economic implications because working in more distant locations generally corresponds to higher wages. Our data show that the average off-farm wages are approximately 30% lower for workers within their home provinces compared to those working outside. Therefore, the change in migration patterns represents an inefficiency created by the program and could have partially offset its positive effects on income. We will quantify the welfare loss from the cross-province reimbursement constraints in the structural model presented in the next section.

[5]Due to data limitations, we cannot examine migration distance of rural labor.

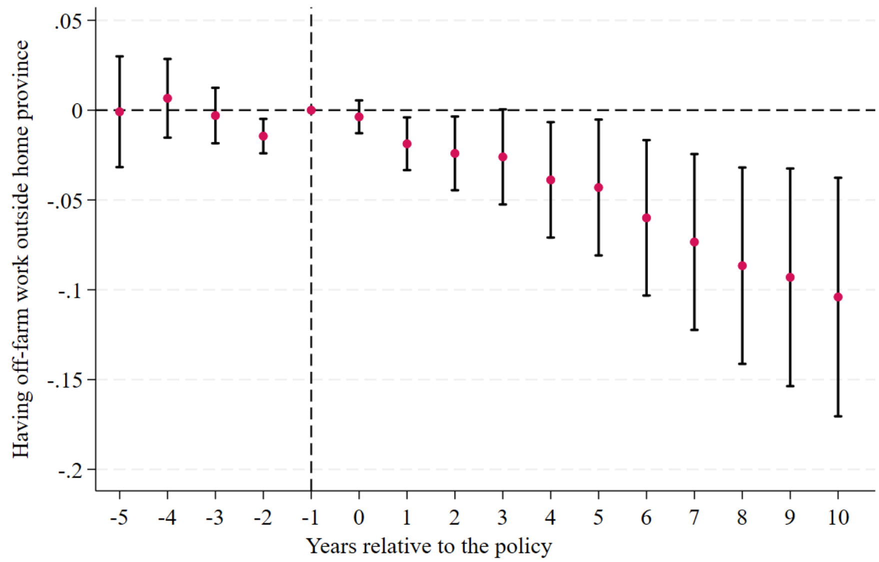

Figure 12: Effect of NCMS on migration pattern

Notes: This figure presents the effect of NCMS on the probability of having off-farm work outside the home province (relative to inside the home province), estimated using model (1). The dependent variable is a dummy variable that equals 1 for individuals with off-farm work outside the home province and 0 for those with off-farm work within the home province. The capped spikes present the 95% confidence interval.

4.4 Return on policy investments

We calculate the return on government investment by comparing NCMS subsidies with their impact on income. Based on the per capita subsidy data presented in Figure 1, we estimate that the program's average per capita subsidy during the sample period was 164.5 Yuan. Using the dynamic effect estimates from Panel A of Figure 5 and accounting for the average household size of 3.9, we calculate an average per capita income effect of 1,126.4 Yuan over the same period. This implies that the government's NCMS investment yields an approximate 6.8-fold return. The calculation remains largely unaffected when incorporating increases in household health expenditures, as the effect on individual health spending is minimal (Panel B of Figure 5). We note that this estimate likely understates the true return on investment, as it excludes additional NCMS benefits such as utility gains from improved health status and increased life expectancy.

5 Potential Gains from Policy Adjustment

Two facts highlighted in Subsection 2.2 motivate us to examine the potential gains from adjusting the current design of NCMS. First, although reimbursement rates under NCMS have increased significantly over time, they remain low—especially for outpatient services and expenditures in high-tier hospitals. Second, significant constraints on cross-province reimbursement persist, including difficulties in claiming medical expenses across provinces and lower reimbursement rates for such claims. This section develops a structural model to examine the potential effects of further increasing reimbursement rates and removing cross-province reimbursement barriers.

5.1 The model

The model characterizes the labor allocation and health investments of utility-maximizing rural residents. Intuitively, the NCMS increases the investment in health, which in turn affects health status, labor productivity, labor allocation, migration patterns, income from different sources, and utility.

5.1.1 Preference

The representative family member of household i maximizes utility derived from income I_i, health h_i, work location d_i, and the disutility of work ϕ_i:

$$U_i(d) = \beta_c \ln I_i + \beta_h h_i + \beta_d d - \phi_i + \epsilon_{id}, \tag{2}$$

where ϵ_{id} is an idiosyncratic work location shock to utility, drawn from an i.i.d. type-I extreme value distribution, and β_c, β_h, and β_d are coefficients to be estimated. To flexibly capture the effect of health insurance on utility through multiple channels, we follow the literature by allowing health, work location, the cost of working, and idiosyncratic shocks to affect utility in a linear and additive form (French and Jones, 2011; Galiani et al., 2015; Lagakos et al., 2023; Mahler and Yum, 2024). We will explain each component of the utility function later.

The model focuses on the utility of a representative family member for each household, and we demonstrate that this specification is particularly useful for model estimation. Specifically, we construct variables for an "average" family member in each household to facilitate estimation. For brevity, we refer to this representative family member simply as "the household" in what follows.

5.1.2 Health determinants and disutility of working

Following Mahler and Yum (2024), we specify the functional forms for health and disutility of working. Health is determined by age, age squared, medical expenditure before reimbursement (M_i), and other unobservable factors (ζ_i):

$$h_i = k_0 + k_1 age_i + k_2 age_i^2 + k_M M_i + \zeta_i, \tag{3}$$

where k_0 represents a constant term, while k_1, k_2, and k_M are coefficients to be estimated. The squared age term captures the nonlinear relationship between health and age.

The disutility of working is specified as:

$$\phi_i = c_a \frac{L_{i,a}^{1+1/\gamma_a}}{1+1/\gamma_a} + c_{na} \frac{L_{i,na}^{1+1/\gamma_{na}}}{1+1/\gamma_{na}}, \tag{4}$$

where γ_a and γ_{na} are curvature parameters that determine the responsiveness of working time, while c_a and c_{na} control the marginal cost of working in agricultural and non-agricultural sectors, respectively. This flexible functional form for the utility cost of work is particularly well-suited for rural settings where both agricultural and off-farm employment coexist.

5.1.3 Labor allocation, medical expenditure, and net income

Households derive income from family-based agricultural production and off-farm work, utilizing their family labor endowment (L_i) and farmland endowment (K_i).[6] Agricultural income ($I_{i,a}$) is determined by the following production function:

$$\ln I_{i,a} = \ln(Ah_i^{\gamma}) + \alpha \ln L_{i,a} + \beta \ln K_i, \tag{5}$$

where A represents total factor productivity, h_i^{γ} captures the productivity effect of health, $L_{i,a}$ denotes labor allocated to agriculture, α and β measure returns to labor and land, respectively. We maintain $\alpha + \beta < 1$ to account for omitted market inputs in this simplified specification.

Households allocate labor ($L_{i,na}$) to off-farm work, earning income:

$$I_{i,na} = w_i L_{i,na}, \tag{6}$$

where the off-farm wage (w_i) depends on health (h_i), working location (d_i), household characteristics (X_i), and unobservables (ξ_i):

$$w_i = \tau_0 + \tau_h h_i + \tau_d d_i + X_i \tau_x + \xi_i. \tag{7}$$

Here, X_i includes family size, gender composition, education levels, and age (with quadratic terms).

Note that the household's time constraint is given by $L_{i,na} + L_{i,a} \leq L_i$. Here, we implicitly assume that the household may allocate some time to leisure, so the time endowment does not necessarily equal the total time allocated to work. Although

[6] This assumption reflects the institutional context of rural China during our sample period, where each household was allocated a fixed area of farmland and efficient land markets were generally absent.

leisure is not explicitly included in the utility function, we use the disutility of working (ϕ_i) to indirectly capture the effect of leisure on utility.

Household net income is given by

$$I_i = I_{i,a} + I_{i,na} - (1 - s_i T_i (1 - d_i)) M_i \ , \tag{8}$$

where M_i represents medical expenditure, and $(1 - s_i T_i (1 - d_i)) M_i$ denotes the medical expenditure after reimbursement. Specifically, T_i is a dummy variable indicating NCMS coverage ($T_i = 1$ if covered), s_i is the reimbursement rate, and d_i is a dummy variable for working location ($d_i = 1$ if working outside the home province). Under the condition that reimbursement applies only to medical expenditures within the home province, we have

$$(1 - s_i T_i (1 - d_i)) M_i = \begin{cases} M_i & \text{if } T_i = 0 \\ M_i & \text{if } d_i = 1, T_i = 1 \\ (1 - s_i) M_i & \text{if } d_i = 0, T_i = 1 \end{cases} . \tag{9}$$

An implicit assumption here is that individuals seek medical treatment only in their province of work. This assumption holds for most illnesses, as the cost of cross-province migration is high relative to medical expenditure.

5.1.4 Equilibrium

The household chooses time allocation ($L_{i,a}$ and $L_{i,na}$), working location (h_i), and health investment (M_i) to maximize household utility (2), subject to the time constraint ($L_{i,na} + L_{i,a} \leq L_i$) and given the functional forms of health production, disutility of work, agricultural production, and off-farm wages presented in equations (3), (4), (5), and (7), respectively.

To focus on the key channels of interest (i.e., labor allocation between sectors, working location, and health investment), our model makes several simplifying assumptions. First, we abstract from labor hiring and land renting in agricultural production, given that most farms in our sample do not hire labor or rent land. Second, we assume that rural residents take off-farm wages as given when making decisions about migration and health investment. Third, we assume that rural residents only utilize medical services in their province of work, given the high costs of temporary migration for medical treatment. We believe that relaxing these assumptions would not significantly alter the model's main predictions.

5.2 Estimation

Before estimating the model, we construct household-level data suitable for estimation. To account for the interdependence of household members and to facilitate estimation, we construct data for a "representative member" of each household. This approach is necessary because agricultural production occurs at the family level, and off-farm work decisions are typically made to maximize family income. Specifically, we define the representative member as the average of each variable for all household members, generating variables such as household average per capita agricultural income, off-farm income, labor supply by sector, and health status. These variables are then used to estimate the model.

Following the literature, we adopt a two-step estimation procedure for the model (French, 2005; French and Jones, 2011). In the first step, we estimate coefficients for the health determination function (3), agricultural production function (5), and wage determination function (7), respectively. In the second step, we estimate the preference parameters in (2) and (4) using the method of simulated moments, which minimizes the distance between model predictions and empirical observations.

To capture the effect of no cross-province reimbursement, we estimate the model using data from before the 2010 reform that introduced cross-province reimbursement. Specifically, we estimate the model using data from the year immediately preceding the policy implementation and the fifth year after implementation. Online Appendix A.5 examines the robustness of our results to alternative data specifications used for estimation. We prespecify the reimbursement rate (s_i) at 50%, which approximates the average reimbursement rate in the fifth year of the policy.

Columns 1–3 of Table 2 present the coefficients from the first step of estimation. The estimations are based on equations (3), (5), and (7), but we additionally control for household fixed effects and year fixed effects in each regression to address potential omitted variable bias. Furthermore, we use the village timing of NCMS as an IV for medical expenditure (M_i) in equation (3) to address the endogeneity of health investment.

The IV estimate of medical expenditure (k_m) suggests that higher medical expenditure due to NCMS significantly improves health. We also find that improved health has a significantly positive effect on off-farm wages (τ_h) but no significant effect on agricultural productivity (γ). These findings are generally consistent with our empirical observation that NCMS primarily increases off-farm income.[7] The estimate of τ_d confirms that individuals with off-farm work outside their province receive higher wages. Finally, we find a high share of returns to land (β) and a relatively low share of returns to labor (α) in the agricultural production function. The estimated coefficients for the agricultural production function should not be directly compared to those in the literature, as we estimate the effects for the "representative" family member.[8]

[7]As noted previously, the increases in per-labor agricultural output could be explained by the mechanical effect of reduced agricultural labor input and do not necessarily reflect increased labor productivity in agriculture.

[8]Specifically, α should be interpreted as the share of return to family-average per capita labor input. Since a large share of family members do not actually work in agriculture, the estimate of α is expected to be smaller than those estimated using actual agricultural labor input data in the literature.

Table 2: Estimated parameters of the structural model

(1) Health		(2) Off-farm wage		(3) Agricultural production		(4) Preference	
k_M	0.2***	τ_h	0.059*	α	0.062***	β_c	1.66***
	(7.59)		(2.16)		(5.30)		(83.00)
k_1	0.064***	τ_d	0.091*	β	0.784***	β_d	1.71***
	(6.40)		(2.13)		(47.44)		(21.38)
k_2	-0.001***			γ	-0.018	β_h	0.40***
	(-8.88)				(-1.07)		(40.00)
						γ_a	1.21***
							(60.50)
						γ_{na}	-1.94***
							(-97.00)
						c_a	1.10***
							(27.50)
						c_{na}	1.69***
							(84.50)

Notes: Columns 1–3 present the estimates for Equations (3), (5), and (7), respectively. All estimations control for household fixed effects and year fixed effects. In Equation (3), medical expenditure (M_i) is instrumented by the village timing of NCMS. The statistics in parentheses are t-statistics. Column 4 presents the estimates for the preference parameters in Equations (2) and (4), obtained using the method of simulated moments.

Column 4 of the table presents the second-step estimates for the vector of preference parameters $\theta = (\beta_c, \beta_h, \beta_d, \gamma_a, \gamma_{na}, c_a, c_{na})$ from (2) and (4). These parameters are estimated using the method of simulated moments, which minimizes the distance between model predictions and empirical observations (Kaboski and Townsend, 2011; Lagakos et al., 2023). Details of the estimation procedure are presented in Appendix A.4.

Briefly, the initial conditions of each agent are fed into the model, and we then solve the utility maximization problem for each agent. Based on the optimized decisions, we compute the simulated means of the four outcome variables: health status, the probability of working outside the home province, agricultural work days, and non-agricultural work days. These simulated moments are then compared to their empirical counterparts under each candidate set of parameters $\hat{\theta}$ to select the optimal estimates. The estimation accounts for the uncertainty in working location (derived from ϵ_{id}) and utilizes the exogeneity from the NCMS rollout for identification.

To demonstrate the goodness of fit of our estimated model, Table 3 compares the observed values of the four key variables with their predicted counterparts based on the initial conditions and the parameter estimates presented in Table 2. The model predictions closely match the observed data, suggesting a good model fit. For example, the predicted health status value is 4.47, while the observed value is 4.48; the predicted off-province working share is 0.159, while the observed value is 0.161.

Table 3: Goodness of fit of the estimated model

Source	Health status	Off-province working share	Off-farm work time share	Agricultural work time share
Model	4.47	0.159	0.33	0.187
Data	4.48	0.161	0.35	0.195

Notes: This table compares the mean values of the four key outcome variables between the observed data and the model predictions.

5.3 Counterfactual analysis

With the estimated model in hand, we are able to examine the counterfactual effects of NCMS under different reimbursement rates and geographic reimbursement constraints. To compare with our empirical findings, we simulate the effects for the four outcome variables of interest: health status, off-farm working location, off-farm work days, and household net income. We simulate the effects for different reimbursement rates ranging from 0.1 to 0.9. For each reimbursement rate, we also simulate the effects with and without cross-province reimbursement constraints.

For the counterfactual of no cross-province reimbursement constraints, the effects are simulated by modifying the out-of-pocket medical expenditure in equation (9) to

$$(1 - s_i T_i) M_i = \begin{cases} M_i & \text{if } T_i = 0 \\ (1 - s_i) M_i & \text{if } T_i = 1 \end{cases} . \tag{10}$$

Recall that since the baseline model is estimated based on data from the period during which no cross-province reimbursement was allowed, the simulated effects for different reimbursement rates from the baseline model reflect the effects with full cross-province reimbursement constraints.

Figure 13 presents counterfactual effects for the four key variables. Consistent with our empirical estimates presented in Section 4, the model predictions suggest that NCMS improved health (Panel A), reduced off-province migration (Panel B), increased off-farm work days (Panel C), and increased net income (Panel D). The magnitude of the estimated effect under the baseline reimbursement rate (0.5) is generally comparable to the corresponding empirical estimate for each variable. These results further support our empirical findings.

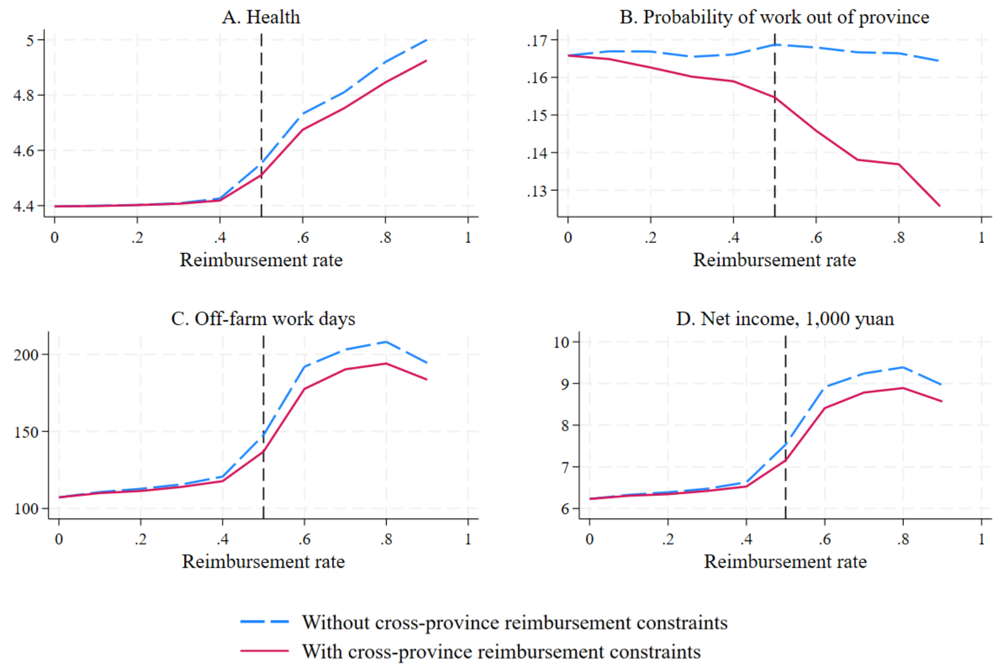

Figure 13: Counterfactual estimates of the effect of NCMS

Notes: This figure presents the counterfactual estimates of the NCMS effect on the four key outcome variables under varying reimbursement rates, comparing scenarios with geographic reimbursement constraints (red lines) and without them (dashed blue lines).

The counterfactual estimates suggest a nonlinear effect of the reimbursement rates on off-farm work and net income. While health levels increase monotonically with the reimbursement rate, off-farm work time and net income first rise and then decline after the rate reaches the threshold of 0.8. The nonlinear effects on income are likely driven by the nonlinear changes in off-farm work time, which, in turn, result from the trade-off between income and the disutility of work. If the government's objective is to increase household income (rather than health alone), the optimal reimbursement rate is approximately 0.8.[9] As detailed in Section 2.2, the current reimbursement rate is generally below 0.8, especially when accounting for the low outpatient reimbursement rate and the low reimbursement rate in high-tier hospitals. Therefore, rural household income in China could be improved by further increasing the current reimbursement

[9]This assessment is based on the fact that the government's investment in NCMS is far smaller than the income gain, as estimated in Section 4.4.

rate.

Finally, the counterfactual estimates for the case of no constraints on cross-province reimbursement suggest that removing cross-province reimbursement constraints could substantially improve both health and income for given reimbursement rates. For each reimbursement rate, health levels, off-farm workdays, and net income are all higher when cross-province constraints are eliminated. The health and income gains from removing these constraints generally increase with the reimbursement rate. Under the optimal reimbursement rate of 0.8, eliminating geographic constraints could increase health gains by 16.4 percent and income gains by 18.7 percent. These additional gains result from removing distortions on inter-provincial migration. Panel B of the figure shows that NCMS has no effect on the likelihood of working outside one's home province when reimbursement constraints are removed. As discussed in Section 2.2, although significant efforts have been made to eliminate geographic constraints, cross-province reimbursement rates remain much lower, and outpatient coverage remains limited. Therefore, our findings suggest that substantial welfare improvements could be achieved by further removing geographic reimbursement constraints in China.

6 Concluding Remarks

This study provides evidence that China's NCMS has generated transformative socioeconomic benefits for rural households. By improving health outcomes across all age groups—raising the probability of being in good health by 4.4% to 8.2%—the program alleviated a critical barrier to economic productivity. The resulting 20.3% increase in household income over a decade underscores the profound interplay between health security and economic mobility. This income growth, driven by expanded off-farm labor participation, higher wages, and enhanced agricultural productivity, demonstrates how public health investments can catalyze multifaceted economic gains. Notably, the aggregate income returns outpaced government expenditures by nearly sixfold, highlighting the program's cost-effectiveness and its potential as a model for scalable rural development initiatives.

The structural model developed in this study not only validates the observed mechanisms but also quantifies opportunities for optimizing policy design. Counterfactual analyses reveal that increasing reimbursement rates to 0.8—a threshold beyond which diminishing returns emerge—could maximize income gains. More critically, removing cross-province reimbursement constraints, which currently distort migration patterns and suppress wages by discouraging interprovincial labor mobility, could amplify income gains by an additional 18.7%. These findings underscore the inefficiencies inherent in localized reimbursement systems and the urgency of integrating regional healthcare networks to unlock fuller economic potential.

For China, these results advocate for targeted reforms: elevating reimbursement rates for outpatient and high-tier hospital services and accelerating the harmonization of cross-province claims processes. For other developing nations, the NCMS experience offers actionable insights. It illustrates how rural health insurance can simultaneously improve welfare and stimulate economic growth, particularly when paired with labor market flexibility.

Bibliography

Babiarz, Kimberly Singer, Grant Miller, Hongmei Yi, Linxiu Zhang, and Scott Rozelle, "New evidence on the impact of China' s New Rural Cooperative Medical Scheme and its implications for rural primary healthcare: multivariate difference-in-difference analysis," *The BMJ*, 2010, *341.*

Bai, Chong-En and Binzhen Wu, "Health insurance and consumption: Evidence from China' s New Cooperative Medical Scheme," *Journal of Comparative Economics*, 2014, *42* (2), 450–469.

Banerjee, Abhijit, Rema Hanna, Benjamin A Olken, and Dmitry Sverdlin Lisker, "Social Protection in the Developing World," *National Bureau of Economic Research*, 2024.

Bartel, Ann and Paul Taubman, "Health and labor market success: The role of various diseases," *The Review of Economics and Statistics*, 1979, pp. 1–8.

Benjamin, Dwayne, Loren Brandt, and John Giles, "The evolution of income inequality in rural China," *Economic Development and Cultural Change*, 2005, *53* (4), 769–824.

Blau, David M, David K Guilkey, and Barry M Popkin, "Infant health and the labor supply of mothers," *Journal of Human Resources*, 1996, pp. 90–139.

Borusyak, Kirill, Xavier Jaravel, and Jann Spiess, "Revisiting event-study designs: robust and efficient estimation," *Review of Economic Studies*, 2024, *91* (6), 3253–3285.

Boyle, Melissa A and Joanna N Lahey, "Health insurance and the labor supply decisions of older workers: Evidence from a US Department of Veterans Affairs expansion," *Journal of Public Economics*, 2010, *94* (7-8), 467–478.

Callaway, Brantly and Pedro HC Sant' Anna, "Difference-in-differences with multiple time periods," *Journal of Econometrics*, 2021, *225* (2), 200–230.

Chari, Amalavoyal, Elaine M Liu, Shing-Yi Wang, and Yongxiang Wang, "Property rights, land misallocation, and agricultural efficiency in China," *The Review of Economic Studies*, 2021, *88* (4), 1831–1862.

Chen, Hua, Yugang Ding, Lin Tang, and Lizhen Wang, "Impact of urban–rural medical insurance integration on consumption: evidence from rural China," *Economic Analysis and Policy*, 2022, *76*, 837–851.

Chen, Yuyu and Ginger Zhe Jin, "Does health insurance coverage lead to better health and educational outcomes? Evidence from rural China," *Journal of Health Economics*, 2012, *31* (1), 1–14.

Cheng, Lingguo, Hong Liu, Ye Zhang, Ke Shen, and Yi Zeng, "The impact of health insurance on health outcomes and spending of the elderly: evidence from China's new cooperative medical scheme," *Health Economics*, 2015, *24* (6), 672–691.

Cheung, Diana and Ysaline Padieu, "Heterogeneity of the effects of health insurance on household savings: Evidence from rural China," *World Development*, 2015, *66*, 84–103.

Das, Jishnu and Quy-Toan Do, "The prices in the crises: What we are learning from 20 years of health insurance in low-and middle-income countries," *Journal of Economic Perspectives*, 2023, *37* (2), 123–152.

DeBrauw, Alan, Jikun Huang, Scott D Rozelle, Linxiu Zhang, and Yigang Zhang, "The evolution of China's rural labor markets during the reforms," 2002.

Fadlon, Itzik and Torben Heien Nielsen, "Family labor supply responses to severe health shocks: Evidence from Danish administrative records," *American Economic Journal: Applied Economics*, 2021, *13* (3), 1–30.

Fink, Günther and Felix Masiye, "Health and agricultural productivity: Evidence from Zambia," *Journal of Health Economics*, 2015, *42*, 151–164.

French, Eric, "The Effects of Health, Wealth, and Wages on Labour Supply and Retirement Behaviour," *The Review of Economic Studies*, 04 2005, *72* (2), 395–427.

— **and John Bailey Jones**, "The effects of health insurance and self-insurance on retirement behavior," *Econometrica*, 2011, *79* (3), 693–732.

Galiani, Sebastian, Alvin Murphy, and Juan Pantano, "Estimating Neighborhood Choice Models: Lessons from a Housing Assistance Experiment," *American Economic Review*, November 2015, *105* (11), 3385–3415.

Garcia-Mandicó, Sílvia, Arndt Reichert, and Christoph Strupat, "The social value of health insurance: Results from Ghana," *Journal of Public Economics*, 2021, *194*, 104314.

Garthwaite, Craig, Tal Gross, and Matthew J Notowidigdo, "Public health insurance, labor supply, and employment lock," *The Quarterly Journal of Economics*, 2014, *129* (2), 653–696.

Gruber, Jonathan, Mengyun Lin, and Junjian Yi, "The largest insurance program in history: Saving one million lives per year in China," *Journal of Public Economics*, 2023, *226*, 104999.

Haushofer, Johannes, Matthieu Chemin, Chaning Jang, and Jeremy Abraham, "Economic and psychological effects of health insurance and cash transfers: Evidence from a randomized experiment in Kenya," *Journal of Development Economics*, 2020, *144*, 102416.

Hokayem, Charles and James P Ziliak, "Health, human capital, and life cycle labor supply," *American Economic Review*, 2014, *104* (5), 127–131.

Huang, Kaixing and Yaxuan You, "Evaluating the impact of the fourth round of China's poverty alleviation program," *American Journal of Agricultural Economics*, 2025.

— **, Jingyuan Guo, and Da Zhao**, "Positive rainfall shocks, overoptimism, and agricultural inefficiency in China," *Journal of the Association of Environmental and Resource Economists*, 2024, *11* (4), 887–919.

Huang, Wei and Hong Liu, "Early childhood exposure to health insurance and adolescent outcomes: Evidence from rural China," *Journal of Development Economics*, 2023, *160*, 102925.

Kaboski, Joseph P. and Robert M. Townsend, "A Structural Evaluation of a Large-Scale Quasi-Experimental Microfinance Initiative," *Econometrica*, 2011, *79* (5), 1357–1406.

Kinnan, Cynthia, Shing-Yi Wang, and Yongxiang Wang, "Access to migration for rural households," *American Economic Journal: Applied Economics*, 2018, *10* (4), 79–119.

Lagakos, David, Ahmed Mushfiq Mobarak, and Michael E. Waugh, "The Welfare Effects of Encouraging Rural–Urban Migration," *Econometrica*, 2023, *91* (3), 803–837.

Lei, Xiaoyan and Wanchuan Lin, "The New Cooperative Medical Scheme in rural China: does more coverage mean more service and better health?," *Health Economics*, 2009, *18* (S2), S25–S46.

Liu, Kai, "Insuring against health shocks: Health insurance and household choices," *Journal of Health Economics*, 2016, *46*, 16–32.

Liu, L and Y Zhang, "Does Non-employment Based Health Insurance Promote Entrepreneurship? Evidence from a Policy Experiment in China," *Journal of Comparative Economics*, 2018, *46*, 270–283.

Mahler, Lukas and Minchul Yum, "Lifestyle Behaviors and Wealth-Health Gaps in Germany," *Econometrica*, 2024, *92* (5), 1697–1733.

Neelsen, Sven, Supon Limwattananon, Owen O'Donnell, and Eddy Van Doorslaer, "Universal health coverage: A (social insurance) job half done?," *World Development*, 2019, *113*, 246–258.

Pauly, Mark V, Peter Zweifel, Richard M Scheffler, Alexander S Preker, and Mark Bassett, "Private health insurance in developing countries," *Health Affairs*, 2006, *25* (2), 369–379.

Raza, Wameq A, Ellen Van de Poel, Arjun Bedi, and Frans Rutten, "Impact of community-based health insurance on access and financial protection: evidence from three randomized control trials in rural India," *Health Economics*, 2016, *25* (6), 675–687.

Sun, Liyang and Sarah Abraham, "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects," *Journal of Econometrics*, 2021, *225* (2), 175–199.

Wagstaff, Adam and Magnus Lindelow, "Can insurance increase financial risk?: The curious case of health insurance in China," *Journal of Health Economics*, 2008, *27* (4), 990–1005.

_ , _ , Gao Jun, Xu Ling, and Qian Juncheng, "Extending health insurance to the rural population: an impact evaluation of China's new cooperative medical scheme," *Journal of Health Economics*, 2009, *28* (1), 1–19.

Wang, Zhen, Zhi Wu, and Yan Yuan, "We' ve got you covered! The effect of public health insurance on rural entrepreneurship in China," *Journal of Public Economics*, 2024, *235*, 105150.

You, Xuedan and Yasuki Kobayashi, "The new cooperative medical scheme in China," *Health Policy*, 2009, *91* (1), 1–9.

A Appendix for Online Publication

A.1 Additional robustness check

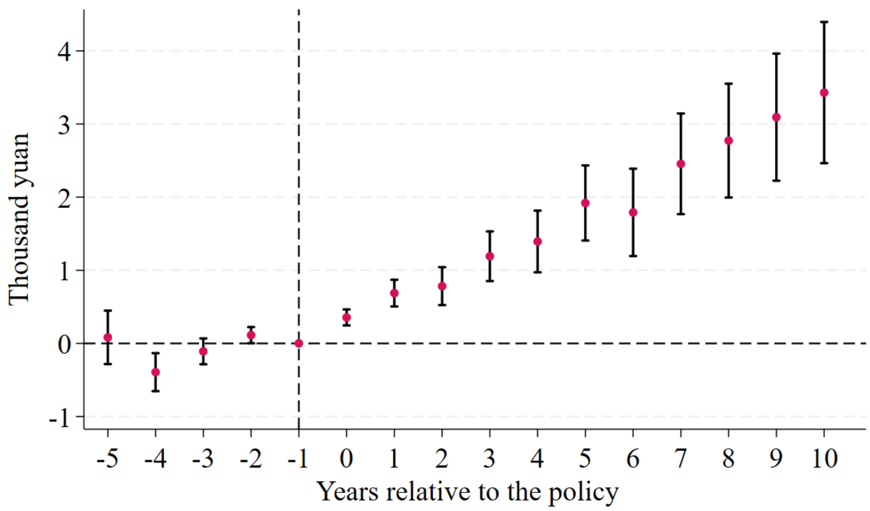

Figure A1: Robust to using per capita income as the dependent variable
Notes: This figure presents the estimates of a version of model (1) that uses net income per capita as the dependent variable. The capped spikes indicate 95% confidence intervals.

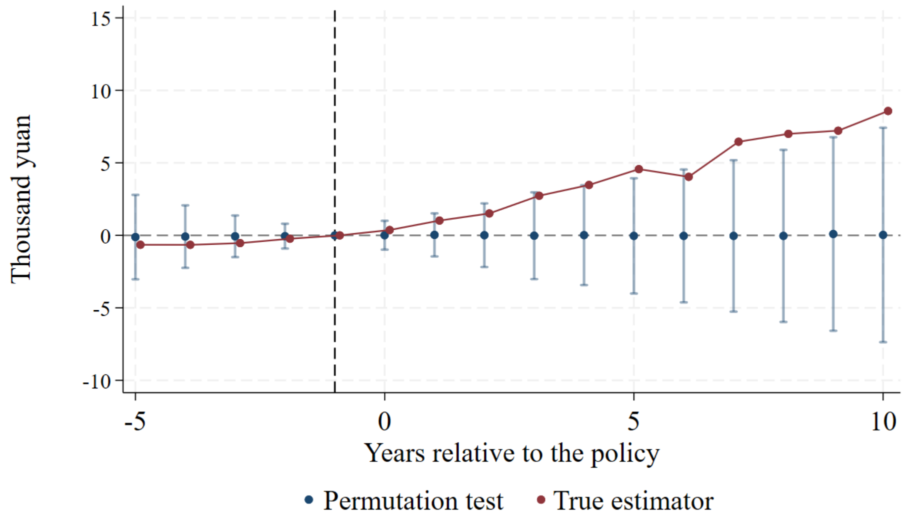

Figure A2: Event study placebo tests

Notes: This figure presents the results of placebo tests for estimating the treatment effect on household net income. First, we randomly reassign the timing of NCMS coverage across villages 100 times. Second, for each permutation, we re-estimate Equation (1). Finally, we generate 100 sets of dynamic treatment effect estimates. The figure displays the 95% confidence intervals for the estimated placebo policy effects in each period relative to the counterfactual policy implementation timing.

A.2 Heterogeneity effect

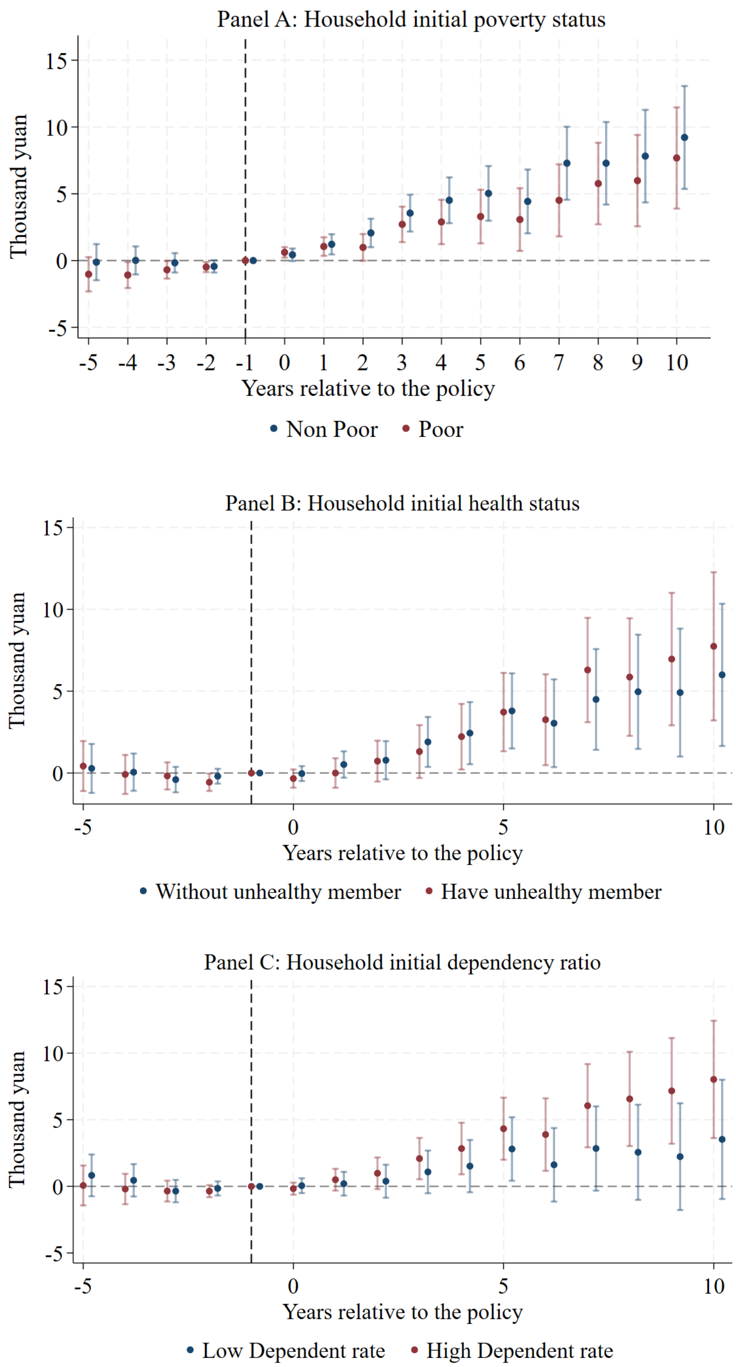

Figure A3: Heterogeneity of the effect on household income.

Notes: This figure presents the heterogeneous effects of NCMS on household net income with respect to initial poverty status (Panel A), initial health status (Panel B), and initial dependency ratio (Panel C). For initial income level and dependency ratio, we classify the sample into two groups based on their median values in year 2000. For initial health status, we classify the sample based on whether the household contained unhealthy individuals or dependent individuals(i.e. age<=16, age>=60 or health status=1) in year 2003. We then estimate income effect for each of these subgroups by interacting the indicators with each of policy time period dummy in model 1. The capped spikes represent the 95% confidence intervals.

A.3 Association between health and labor allocation

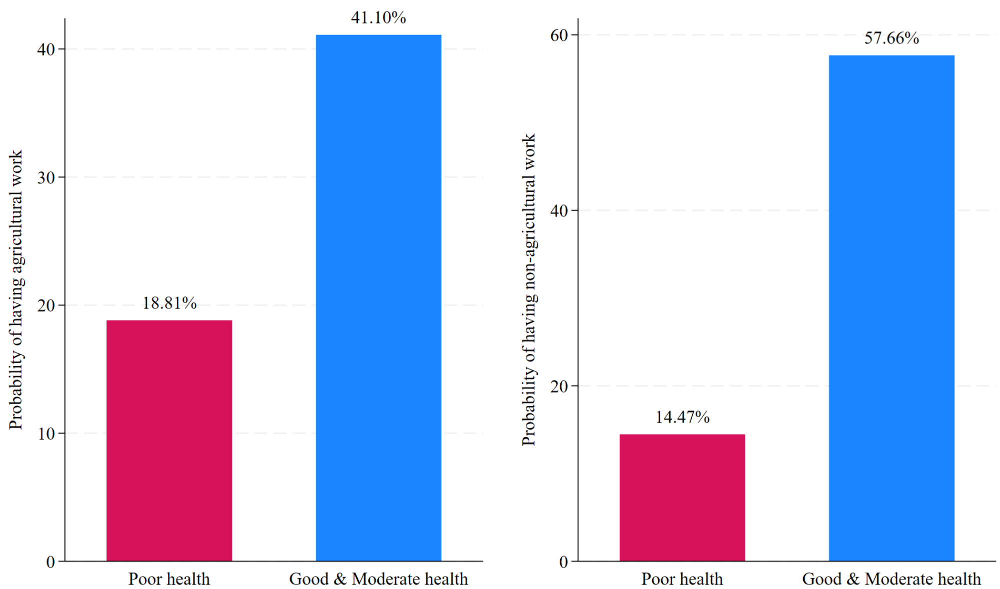

Figure A4: Probability of having agricultural and off-farm work for working-age population with different health conditions

Notes: This figure illustrates the probability of engaging in agricultural and off-farm employment among the working-age population with different health conditions in 2015.

A.4 Methods of moments estimation

We estimate the vector of preference parameters $\theta = (\beta_c, \beta_d, \beta_h, c_a, c_{na}, \gamma_a, \gamma_{na})$ from Equations (2) and (4) using the method of simulated moments, which minimizes the distance between model predictions and empirical observations. The initial conditions of each agent are fed into the model. For each agent, we solve the utility maximization problem over health status, working location, and labor supply in each sector. Based on the optimized decisions, we compute the simulated means of the four outcome variables: health status, the share of family members working outside the home province, agricultural workdays, and non-agricultural workdays. These simulated moments are then compared to their empirical counterparts for each candidate parameter set.

Formally, let $\triangle_{obs}$ denote the observed values of the moments, and $\triangle(\hat{\theta})$ denote the model-implied moments. The method of simulated moments estimator is given by:

$$\hat{\theta}_0 = \arg\min_{\theta} \left(\triangle(\hat{\theta}) - \triangle_{obs} \right)' V \left(\triangle(\hat{\theta}) - \triangle_{obs} \right),$$

where V is a 64×64 weighting matrix. We estimate the variance of $\hat{\theta}$ using the method of (Kaboski and Townsend, 2011).

Next, we define our moment functions. Due to the location shock in the utility function, the probability of working outside the home province for each agent is:

$$\pi_{1,i} = \text{Prob}(d_i^{opt} = 1) = \frac{\exp(V_{d_i^{opt}=1})}{\exp(V_{d_i^{opt}=0}) + \exp(V_{d_i^{opt}=1})}.$$

We account for uncertainty in working location shocks by taking expectations over the state variables:

$$\begin{aligned}
d_i^{model} &= \pi_{1,i}, \\
h_i^{model} &= \pi_{1,i} h_i^{d_i^{opt}=1} + \pi_{0,i} h_i^{d_i^{opt}=0}, \\
L_{i,a}^{model} &= \pi_{1,i} L_{i,a}^{d_i^{opt}=1} + \pi_{0,i} L_{i,a}^{d_i^{opt}=0}, \\
L_{i,na}^{model} &= \pi_{1,i} L_{i,na}^{d_i^{opt}=1} + \pi_{0,i} L_{i,na}^{d_i^{opt}=0}.
\end{aligned}$$

Note that our construction of the representative household member's data ensures that the working location d_i corresponds to the proportion of household members working outside the home province, which aligns directly with the definition of $\pi_{1,i}$. From these equations, we derive the following four moment conditions:

$$\begin{aligned}
&E\left(h_i^{model} - h_i^{obs} \mid (X_i, T_i)\right) = 0; \quad E\left(L_{a,i}^{model} - L_{a,i}^{obs} \mid (X_i, T_i)\right) = 0; \\
&E\left(L_{na,i}^{model} - L_{na,i}^{obs} \mid (X_i, T_i)\right) = 0; \quad E\left(d_i^{model} - d_i^{obs} \mid (X_i, T_i)\right) = 0.
\end{aligned} \tag{11}$$

To further exploit the exogenous variation in the rollout of the NCMS for identification, we note that the moment conditions in moment (11) are defined conditional on NCMS coverage status. By the law of iterated expectations, the unconditional moment conditions obtained by interacting with the policy indicator T_i must also equal zero:

$$
\begin{aligned}
&E\left(T_i(h_i^{model} - h_i^{obs}) \mid (X_i, T_i)\right) = 0; \quad E\left(T_i(L_{a,i}^{model} - L_{a,i}^{obs}) \mid (X_i, T_i)\right) = 0; \\
&E\left(T_i(L_{na,i}^{model} - L_{na,i}^{obs}) \mid (X_i, T_i)\right) = 0; \quad E\left(T_i(d_i^{model} - d_i^{obs}) \mid (X_i, T_i)\right) = 0.
\end{aligned}
\tag{12}
$$

By minimizing the eight moment conditions in moment (11) and moment (12), we fully identify the seven parameters $\theta = (\beta_c, \beta_d, \beta_h, c_a, c_{na}, \gamma_a, \gamma_{na})$. To reduce computational complexity, we randomly select 2,000 observations from the full sample for estimation.

A.5 Robust to the data used for estimation

As a robustness check, we estimate the model using data from different periods relative to the policy implementation while maintaining the reimbursement rate consistent with our baseline model. Specifically, we utilize data from the period immediately preceding the policy and the third year following the policy. The resulting counterfactual estimates, presented in Figure A5, demonstrate strong comparability with those shown in the main text.

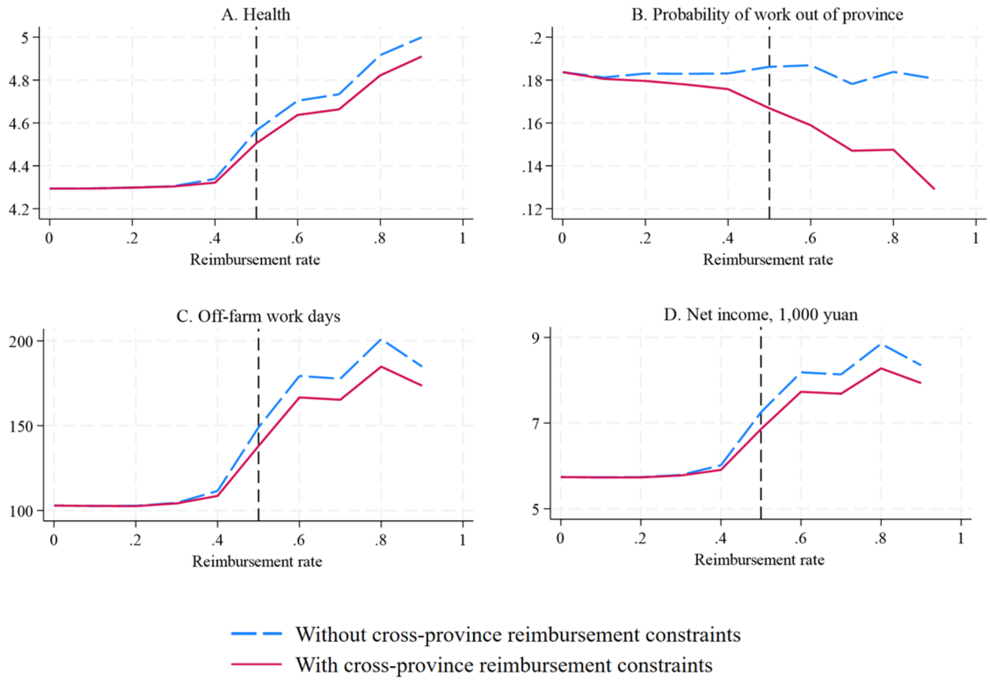

Figure A5: Counterfactual estimates of the effect of NCMS

Notes: This figure presents the counterfactual estimates of the NCMS effect on the four key outcome variables under varying reimbursement rates, comparing scenarios with geographic reimbursement constraints (red lines) and without them (dashed blue lines). The parameters are estimated using data from the period immediately before the policy implementation and the third year after the policy.