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Beyond Medical Care: Assessing the Impact of Health Insurance Premium Subsidy Policy on Calorie Consumption and Physical Productivity in China

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Beyond Medical Care: Assessing the Impact of Health Insurance Premium Subsidy Policy on Calorie Consumption and Physical Productivity in China

Yunze Han^{1*}, Kei Kajisa¹

Abstract

Research on the effectiveness of health insurance premium subsidy policies on human capital primarily focuses on the direct pathways of increased medical utilization and subsequent improvements in health capital. However, such policies can also increase the budget for nonmedical expenditures, some of which can be converted into labor productivity, thereby forming an indirect pathway. This study used the New Rural Cooperative Medical Scheme (NRCMS) in China to investigate an indirect pathway through which the health insurance subsidy policy enhances labor productivity by increasing food consumption and caloric intake. The NRCMS, launched in 2003, provides health insurance subsidies to rural residents to alleviate the financial burden of health issues and improve nonmedical consumption. Using unbalanced panel data from 2009 and 2011 of the China Health and Nutrition Survey, this study tested two hypotheses. First, participating in the NRCMS increases individuals' caloric intake. Second, increased caloric intake enhances productivity, as measured by earnings per working day. We used propensity score matching for the first hypothesis to handle the endogeneity of program participation and the inverse probability weighting regression for the second hypothesis to control for the unbalanced structure of the panel dataset. We found that the NRCMS significantly increased caloric intake by approximately 255 kcal, subsequently enhancing labor productivity by around 2.58%–3.39% in rural China in the late 2000s. This study contributes to our understanding of the impact of health insurance policies on poverty alleviation.

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1. Introduction

Grossman (2000) posited that two types of human capital jointly affect income: health capital, which determines the total healthy time available for labor participation (Grossman, 1972; Stewart et al., 2007; Kankeu et al., 2013; Schofield et al., 2015), and productivity-related capital, which determines the earnings per unit of labor time (Mazumdar, 1959).² Both types of human capital among vulnerable groups suffer from underinvestment owing to the financial burden of health issues. Regarding health capital, medical care is often unaffordable (Peters et al., 2008; Wagstaff et al., 2009). Regarding productivity-related capital, high medical expenses limit the budget for nonmedical consumption, such as for food (Asfaw & Braun, 2004; Wagstaff, 2007), in which the calorie content may be crucial for maintaining productivity (Strauss, 1985, 1986; Jha et al., 2009).³ In response, many governments have implemented policies that provide health insurance premium subsidies to vulnerable groups to reduce their financial burdens (Spaan et al., 2012).

Studies have demonstrated the overall impact of health insurance subsidy policies that effectively increase income or reduce the incidence of poverty among vulnerable groups (Korenman & Remler, 2016; Chen et al., 2017; Remler et al., 2017). Under Grossman's human capital framework, the underlying mechanism driving this impact may involve two pathways: a direct pathway through increased medical care utilization to boost health capital and an indirect pathway by expanding the budget for nonmedical consumption, such as calories, to enhance productivity. Previous studies have primarily focused on the direct pathway, establishing the "policy to health capital" linkage. Specifically, research has shown that such policies increase access to outpatient medical care (Sparrow et al., 2013; Chen et al., 2014; Artignan & Bellanger, 2021), inpatient medical care (Ghislandi et al., 2015), and preventive healthcare services (Miller et al., 2013). Moreover, increased medical utilization makes individuals healthier (Quimbo et al., 2011; Sood et al., 2014). These studies support the existence of the direct pathway. Additionally, such policies reduce individuals' total medical expenses (Babiarz et al., 2010; Nguyen et al., 2012) and

² Beyond Grossman's definition of health capital, which was originally intended for his modeling purpose, health capital may influence income via productivity improvement. This has been discussed in Section 3 of this article by presenting a more flexible framework.

³ While food is also related to health, this study primarily focused on the role of caloric intake in maintaining productivity. The causal figure in Section 3 accounts for this issue, without affecting the studied causal relationships.

precautionary savings (Gruber & Yelowitz, 1999; Cheung & Padieu, 2015). These findings imply that individuals could have a bigger budget for nonmedical expenditures, including food, suggesting the existence of an indirect pathway for productivity-related capital.

A potential causal linkage of the indirect pathway is that the policy increases caloric intake, which subsequently boosts productivity. However, no evidence confirms the presence of this pathway. First, while some studies have demonstrated that such policies increase overall food consumption (Hamid et al., 2011; Asfaw et al., 2022) or improve the dietary structure (Chen et al., 2022), they have not specifically addressed the increase in caloric intake. Second, even if caloric intake increases, it does not necessarily convert to productivity as its validity varies by region, developmental stage, and population group (Deolalikar, 1988; Thomas & Strauss, 1997; Jha et al., 2009). Consequently, further research is needed to validate the calorie and productivity components to identify the indirect pathway. Understanding this pathway could reveal that the policy's income-increasing mechanism might extend beyond medical care and health capital, potentially influencing productivity through nonmedical consumption factors, such as caloric intake.

This study aimed to identify the indirect pathway by evaluating the New Rural Cooperative Medical Scheme (NRCMS) in China. The NRCMS is an insurance subsidy policy initiated by the Chinese government in 2003, targeting rural residents. The program is co-funded by individuals, rural communities, and government subsidies. It initially covered hospitalization and critical illness and gradually expanded its coverage. Participation in the program is voluntary. The goal of the NRCMS extends beyond increasing access to medical care and aims to increase nonmedical consumption (Bai & Wu, 2014).

This study proposed two hypotheses to explore the indirect pathway. The first hypothesis was that the NRCMS would increase individuals' calorie consumption in the year of participation. The second hypothesis was that calorie consumption in the year of participation would enhance productivity in the following year. Productivity was measured as earnings per working day.

The China Health and Nutrition Survey (CHNS) database, an unbalanced panel dataset that has collected individual information every two to four years from 1989 to 2015, allowed us to examine these two hypotheses. For the first hypothesis, we used the variables

of program participation and calorie consumption from the 2009 survey wave of the CHNS. For the second hypothesis, we used the “total income for 2010” divided by the “number of working days in 2010” recorded in the 2011 survey wave.⁴ This enabled us to calculate the productivity for 2010 and match this productivity data with the 2009 data to assess whether caloric intake in 2009 influenced labor productivity in 2010. The panel data structure of the dataset allowed us to use past caloric intake as a determinant of the following year’s productivity, through which we could circumvent reverse causality from higher productivity to more calorie consumption.

This study’s empirical strategy for the first hypothesis was to apply propensity score matching (PSM) to avoid self-selection bias in participation in the subsidy program. For the second hypothesis, this study used inverse probability weighting (IPW) regression to control for the attrition bias resulting from matching productivity data from the unbalanced panel dataset. We found that the NRCMS significantly increased caloric intake by approximately 255 kcal, subsequently enhancing labor productivity by around 2.58%–3.39%. These results support the existence of an indirect pathway through which the NRCMS enhances labor productivity by increasing the calories.

This study contributes to the literature in two ways. First, it enhances our understanding of how subsidizing health insurance policies facilitates poverty alleviation among vulnerable populations. While research has shown that such policies increase income or reduce the incidence of poverty among vulnerable groups (Korenman & Remler, 2016; Chen S et al., 2017; Remler et al., 2017), the underlying human capital mechanisms still need to be elucidated. Beyond the direct pathway established through medical care and health capital in previous research, this study constructed an indirect pathway in which the policy encourages rural residents in China to purchase more calories, thereby enhancing their productivity-related capital.

Second, this study deepens our understanding of calories as productivity-related capital. Previous research has deliberately avoided considering calorie increase as a positive indicator of policy evaluation (Chen et al., 2022), primarily because calories do not necessarily equate to a good diet (Mihaylova et al., 2023). While this study did not

⁴ The original question on the number of working days in the CHNS was, “For how many days in a week, on average, did you work?” Based on this question, we can calculate the total working days.

dispute this perspective, it emphasized that if calories are viewed within the framework of human capital and production, they can still be crucial, particularly in situations where physical labor is the main source of subsistence-level income; this was the situation at our study site during the survey period. This understanding suggests that the effectiveness of calories as a positive outcome significantly depends on whether the policy's target population is at a stage where the marginal effect of calories on productivity is significant and positive.

The remainder of this article is organized as follows. Section 2 introduces the background of the NRCMS, Section 3 introduces the hypotheses, Section 4 presents the data and empirical strategy, Section 5 presents the results, and Section 6 concludes the study.

2. Background

In the late 1950s, to address the difficulty rural populations faced in accessing medical care, the Chinese government began establishing the Cooperative Medical System (CMS) (Chen et al., 1993). The system operates primarily through funding from rural communities, with additional contributions from individuals and government subsidies to establish health centers and provide medicines, allowing rural populations to access affordable medical services (Feng et al., 1995). By the 1970s, the CMS covered 90% of China's rural population and became one of the most successful examples of addressing healthcare issues in developing countries (Zhang & Unschuld, 2008; You & Kobayashi, 2009). However, by the 1980s, due to reforms in China's rural economic system, private production replaced collective agricultural production, causing the CMS to lose its primary funding source and collapse (Sidel, 1993; Liu, 2004). By 1998, insurance coverage for the rural population in China had dropped to just 9.5% (Liu, 2004).

Against this backdrop, the financial burden of health issues became the leading cause of poverty in rural China in the 1990s (Peng et al., 2019). This poverty is not merely a short-term financial loss due to out-of-pocket health expenditures but also a long-term poverty trap that hinders human capital accumulation. First, rural populations without CMS find it difficult to obtain adequate medical care, leaving their health unguaranteed (Liu et al., 1995). Second, food consumption is significantly reduced owing to the lack of health

insurance (You & Kobayashi, 2009), which leads to low labor productivity in rural China (You et al., 2018).

To mitigate this issue, the Chinese government launched the NRCMS in 2003 with the goal of increasing the utilization of medical care and nonmedical consumption (Bai & Wu, 2014), both of which can potentially enhance human capital. The NRCMS is funded jointly by individuals, rural communities, and government subsidies, providing rural populations with health insurance at below-market prices and allowing voluntary participation. In the initial years after its introduction, the NRCMS was implemented in only a few provinces, and participants could receive reimbursements only if they sought care in a limited number of designated hospitals (Watts, 2006; Huang et al., 2011). By 2008, with increased funding from the central government, the NRCMS expanded to all provinces and lifted the restrictions on designated hospitals (Watts, 2006; Huang et al., 2011).

3. Hypotheses

Income is constrained by the time endowment available for labor work and productivity. Perspectives on the role of human capital have evolved over time. Becker (1964) argued that all forms of human capital constitute productivity. An implicit assumption here is that time endowment is a fixed constant (e.g., 365 days a year). By contrast, Grossman (1972) proposed that time endowment should be the total healthy time—a function of health capital—rather than a constant. Therefore, he distinguished health capital as a separate category of human capital that determines the healthy time available for labor participation. Meanwhile, other forms of human capital are considered productivity-related capital. The Grossman model has become one of the foundations for subsequent health economics modeling (Muurinen, 1982; Eisenring, 1999; Leibowitz, 2004).

Poor people remain trapped in poverty because they are unable to invest in sufficient human capital (Ghatak, 2015). Empirical research has demonstrated the consequences of insufficient levels of both types of human capital, as proposed by Grossman, especially among laborers who primarily rely on physical labor. First, insufficient health capital is known to lead to reduced labor time (Stewart et al., 2007; Kankeu et al., 2013; Schofield

et al., 2015). Second, insufficient productivity-related capital, such as calories for physical labor, leads to low earnings per unit of labor time (Jha et al., 2009). These findings suggest two potential strategies for poverty alleviation through policy interventions: improving health and productivity-related capital.

In rural China, the NRCMS aims to increase medical care and nonmedical consumption, which may simultaneously enhance health and productivity-related capital. With the exception of the dashed lines, Figure 1 illustrates the potential mechanisms advanced within Grossman's framework. Medical care is a critical investment of health capital (Leibowitz, 2004). The NRCMS may increase health by enhancing the utilization of medical care. This pathway is widely considered the direct impact of such policies (Pan et al., 2016). Some nonmedical consumption, especially of food, is not only possibly related to health, but, more importantly, its caloric content may be a crucial investment for maintaining productivity, particularly among physical laborers (Strauss, 1985, 1986; Jha et al., 2009). Therefore, a potential indirect pathway is to enhance productivity by increasing the caloric intake.

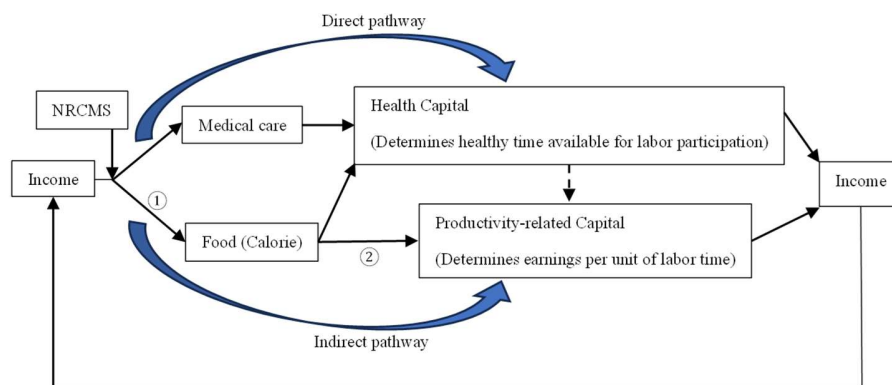


Figure 1. Potential mechanisms of health insurance subsidies in enhancing human capital

Although research has shown that the NRCMS has reduced poverty incidence (Li et al., 2015; Peng et al., 2019), the underlying human capital mechanisms remain unclear. Research on the NRCMS in China has primarily focused on the direct pathway (Cheng et

al., 2015; Dai et al., 2016). Studies on analogous policies in other countries have predominantly addressed this pathway (Quimbo et al., 2011; Sood et al., 2014). In either context, indirect pathways are yet to be explored. The NRCMS presents a valuable opportunity to fill this gap by providing a comprehensive understanding of the human capital mechanisms underlying health insurance subsidies.

To verify the indirect pathway of productivity, this study tested two hypotheses, as explained in Section 1. Hypothesis 1 (Participating in the NRCMS increases individuals' calorie consumption in the year of participation) corresponds to “①” in Figure 1. Hypothesis 2 (Calorie consumption in the year of participation enhances productivity in the following year) corresponds to “②” in Figure 1. The validation of both hypotheses would indicate that the NRCMS reduces poverty by influencing labor productivity through caloric intake.

Another point to discuss is whether it is entirely reasonable to use Grossman's assumption that treats health and productivity-related capital as two independent types of human capital. In reality, health capital may not only determine the number of healthy days but also could potentially become a part of productivity, as indicated by the dashed line in Figure 1. Although this possibility does not affect the research hypothesis of the indirect pathway in this study, it may lead to the omitted variable bias when testing Hypothesis 2 because of the insufficient inclusion of health-related variables. To address such concerns, we adopted the following approach. We presented the main regression results without including health-related control variables and added a health indicator to the model to examine whether its inclusion affects the estimates of the main regression.

4. Data and Empirical Strategy

4.1 Data

We used the data from the CHNS.⁵ The CHNS was established by the Carolina Population Center at the University of North Carolina at Chapel Hill and the National Institute for Nutrition and Health at the Chinese Center for Disease Control and Prevention. The survey collects data from 15 provinces of China using multistage cluster sampling

⁵ The CHNS's official website: <https://www.cpc.unc.edu/projects/china>.

methods.⁶ It includes variables necessary for this study, such as individual characteristics, NRCMS participation, caloric intake, income, and working days. The database consists of surveys conducted every two to four years since 1989, with the nutritional data updated until 2011. The CHNS attempts to follow up with each sample in every survey wave. For samples that are no longer tracked, besides those unwilling to continue participating, those who migrate to non-survey areas are also excluded. To compensate for this attrition, the CHNS selects new families to add to the sample and ensure the sufficient sample size.

We screened the data based on the following criteria. First, only individuals with an agricultural household registration were retained as they are the target population of the NRCMS. Second, only individuals aged 18–60 were included as they form the primary income-generating age group. The age of 18 years is the legal age of adulthood in China, and 60 is the legal threshold for old age. Third, abnormal samples were excluded, including those with a daily caloric intake exceeding 8,000 kcal, a weight less than 30 kg, and a height less than 80 cm.

Accordingly, this study used the 2009 wave data to verify Hypothesis 1 (i.e., Participating in the NRCMS increases individuals' calorie consumption in the year of participation). Subsequently, we used income in 2010 divided by the working days in 2010, both of which were recorded in the 2011 wave, to represent the productivity of 2010. Because income per unit of time is typically a direct reflection of labor productivity (Feldstein, 2008), previous empirical studies have used this approach to indicate productivity (Sahn & Alderman, 1988; Jha et al., 2009). Productivity in 2010 was matched with the calorie data from the 2009 wave to verify Hypothesis 2. Although the sample data were collected more than a decade ago, we believe that this study is relevant because we can draw insights for many developing countries at a developmental stage similar to that of China a decade ago.

4.2 Empirical Strategy

4.2.1 Propensity Score Matching

⁶ The CHNS continually expands the provinces in its sample. The 2009 wave included 9 provinces, the 2011 wave included 12 provinces, and the 2015 wave includes 15 provinces.

Hypothesis 1 examined the treatment effect of the NRCMS on calorie consumption in 2009. Because NRCMS participation is voluntary rather than randomly assigned, there is a self-selection issue. This study adopted the PSM approach by referencing the methods used by Trujillo et al. (2005) and Sun and Lyu (2020) to evaluate the impact of health insurance policies.

We followed the standard PSM approach (Caliendo & Kopeinig, 2008). First, we generated a propensity score using a probit model of NRCMS participation based on a set of individual characteristics, including the previous year's income, education, age, sex, marital status, height, weight, and regional dummy variables.⁷ Second, this study used single nearest-neighbor matching without replacement to match similar individuals in the treatment (NRCMS participants) and control (NRCMS non-participants) groups. Third, we examined the matching results to ensure that they met the two basic assumptions of PSM: balancing property and common support. Finally, the average treatment effect on the treated (ATT) was calculated using the following formula:

$$ATT = E(Calorie_1|P(X), NRCMS = 1) - E(Calorie_0|P(X), NRCMS = 1) \quad (1)$$

where calorie represents an individual's caloric intake, X denotes individual characteristics condensed into a propensity score P , and NRCMS indicates program participation (1 for participation and 0 for non-participation). The first term on the right-hand side of the equation represents the average caloric intake of the treatment group (NRCMS = 1) after matching, and the second term represents the counterfactual caloric intake for the treatment group.

Similarly, the average treatment effect on the untreated (ATU) was calculated as follows:

$$ATU = E(Calorie_1|P(X), NRCMS = 0) - E(Calorie_0|P(X), NRCMS = 0) \quad (2)$$

Combined with the ratio of people in the two groups p , the average treatment effect (ATE) was calculated as:

$$ATE = p(NRCMS = 1) \times ATT + p(NRCMS = 0) \times ATU \quad (3)$$

⁷ The regional dummies were based on China's seven geographic regions. Among the nine provinces in the 2009 wave, Jiangsu and Shandong were in East China; Henan, Hubei, and Hunan were in Central China; Guangxi was in South China; Guizhou was in Southwest China; and Liaoning and Heilongjiang were in Northeast China. Thus, although the CHNS included only 9 of the 34 provinces in 2009, it represented 5 out of the 7 geographic regions, providing a certain degree of generalizability.

4.2.2 Inverse Probability Weighting Regression

To test Hypothesis 2, caloric intake data from 2009 and productivity data from 2011 were used, based on an unbalanced panel dataset. The attrition between the two datasets was likely to be nonrandom, as explained earlier. Therefore, relying solely on OLS estimates may be insufficient. A practical method for mitigating attrition bias is the IPW regression (Wooldridge, 2007; Matsouaka & Atem, 2020; Carry et al., 2021). We used a logit model to estimate the likelihood that individuals who participated in the 2009 survey would continue to participate in 2011. The dependent variable was continued participation (1 for participation in both 2011 and 2009, and 0 for participation in 2009 only), and the independent variables were individual characteristics in 2009. The weights w were generated based on the estimated probability of continued participation. Finally, the impact of caloric intake on productivity was estimated using the following formula:

$$\min_{\alpha, \beta, \gamma} \sum_{i=1}^n w_i (\log(Productivity_i) - (\alpha + \beta Calorie_i + \sum_{k=1}^K \gamma_k Control_{ik}))^2 \quad (4)$$

where i represents the individual, and k denotes the suffix for the regression coefficient γ . *Productivity* represents labor productivity in 2010, *Calorie* indicates caloric intake in 2009, and *Control_k* comprises a set of control variables. In the main regression, the control variables include age, sex, education, marital status, height, weight, and regional dummies. The coefficient of our interest ($\beta \times 100$) represents the percentage increase in productivity per unit increase in caloric intake, given that the dependent variable is the log of productivity.

Beyond the main regression, additional control variables, including a health indicator and labor productivity in 2008, were introduced to ensure robustness. Controlling health is necessary because, as mentioned in Section 3, using Grossman's (1972) assumption may not fully capture reality, as health capital's impact on income may not be limited to healthy days and may also affect productivity. The CHNS database records the number of sick days an individual had 28 days before the survey interview, which can be used as a health indicator. Including labor productivity in 2008 can further mitigate the potential omitted variable bias. This variable was calculated by dividing an individual's total income in 2008 by the total number of working days in 2008, as recorded in the 2009 wave of the CHNS.

5. Results

5.1 Descriptive Statistics

Table 1 presents the definitions and descriptive statistics of the variables from the 2009 wave dataset used for Hypothesis 1. The outcome variable was calorie, with an average value of approximately 2,268 kcal. The sex differences in caloric intake (not shown in the table) indicate that males consumed approximately 2,451 kcal per day, whereas females consumed approximately 2,066 kcal per day. According to the Chinese Dietary Reference Intake (2013) standards, the calorie requirements for moderate physical laborers, such as waiters and salespersons, are 2,250 kcal for men and 1,800 kcal for women. The requirements for heavy physical laborers, such as farmers and workers, are 3,000 kcal for men and 2,350 kcal for women.⁸ This indicates that in 2009, the rural population in China generally had a relatively low nutritional intake, barely sufficient for moderate physical labor and insufficient for heavy physical labor. Therefore, if the rural population had a higher budget for nonmedical consumption, they might have considered increasing their caloric intake. Moreover, increasing caloric intake could make them more capable of performing physical labor, particularly in the case of heavy physical labor, thus improving their labor productivity.

Table 1 also includes individual characteristics. The rural population's total income in the year before the 2009 survey averaged approximately 14,000 yuan. This amount was less than half of the 2008 urban per capita income of 29,229 yuan, indicating a deficiency.⁹ Additionally, the average number of years of education was only 7.15 years, equivalent to the first year of junior high school, which was also extremely low.

As NRCMS participation is voluntary rather than randomly assigned, participants and non-participants exhibited significant differences in their characteristics. These differences are presented in Table 2. Our *t*-test for mean differences indicated that participants had significantly lower income and education levels than non-participants, suggesting that

⁸ In nutrition science, the quantitative method for measuring the degree of physical exertion is called the physical activity level. According to the Chinese dietary reference intakes (2013), China classifies physical jobs into light, moderate, and heavy levels.

⁹ Data source: National Bureau of Statistics of China. Retrieved from https://www.stats.gov.cn/sj/zxfb/202303/t20230301_1919501.html.

disadvantaged groups were more inclined to join the NRCMS. Participants were also significantly older, likely because the financial burden of health issues increases with age (Caley & Sidhu, 2011). Furthermore, participants had significantly lower height and weight, which suggests food insecurity, as height usually reflects food intake in early life (Deaton, 2007) and weight is related to past calorie accumulation (Saris, 2001). Overall, the differences between participants and non-participants, as shown in Table 2, highlight the rationale for using PSM.

Table 1. Definition and descriptive statistics of variables from the wave 2009 data set for Hypothesis 1.

Variables	Definition	Mean	SD	min	max
Calorie	Average caloric intake of the respondent in a single day (100 kcal)	22.68	6.56	5.59	69.41
Income	Annual total income before the survey year (1000 yuan)	13.98	25.07	-121.60	600.00
Education	Years of education	7.15	3.30	0	16
Age	Age of the respondent	43.25	10.45	18	60
Male	1 for male, 0 for female	0.52	0.50	0	1
Married	1 for married, 0 for other	0.90	0.30	0	1
Height	Height of the respondent (cm)	161.93	8.18	138.40	186.50
Weight	Weight of the respondent (kg)	60.95	10.75	34.00	103.70

Data source: CHNS 2009 survey wave.

Note: Some income data are negative due to losses from own land farming or livestock production. Sample size: n=2810.

Table 2. Differences in characteristics between NRCMS participants and non-participants in 2009.

Variables	Participants		Non-Participants		Mean difference
	Mean	Std. Dev.	Mean	Std. Dev.	<i>p</i> -value
Income	13.66	24.95	20.70	26.70	0.00
Education	7.03	3.23	9.71	3.60	0.00
Age	43.44	10.36	39.29	11.47	0.00
Male	0.52	0.50	0.59	0.49	0.13
Married	0.91	0.29	0.82	0.38	0.00
Height	161.81	8.19	164.30	7.76	0.00
Weight	60.80	10.69	64.15	11.47	0.00

Data source: CHNS 2009 survey wave.

Note: The *p*-value indicates the result of a *t*-test comparing the means of characteristics between participants and non-participants. Sample size: n=2810.

Table 3. Definitions and descriptive statistics for Hypothesis 2 (2009 data combined with 2010 productivity).

Variables	Definition	Mean	SD	min	max
Productivity	Total income divided by working days in 2010 (yuan/day)	80.41	125.12	-187.21	2115.87
Calorie	Average caloric intake of the respondent in a single day (100 kcal)	23.05	6.61	6.14	53.22
Education	Years of education	7.06	3.22	0	16
Age	Age of the respondent	44.01	8.76	18	58
Male	1 for male, 0 for female	0.52	0.50	0	1
Married	1 for married, 0 for other	0.94	0.23	0	1
Height	Height of the respondent (cm)	161.86	8.27	138.60	186.50
Weight	Weight of the respondent (kg)	61.40	11.08	34.00	103.70

Data source: CHNS 2009, 2011 survey wave.

Note: Some income data are negative due to losses from own land farming or livestock production, which in turn causes negative productivity. Sample size: n=1611.

Table 3 presents the definitions and descriptive statistics for Hypothesis 2. Owing to sample attrition, the sample size decreased from 2,810 to 1,611 participants, resulting in an attrition rate of approximately 40%. This level of attrition was likely to cause bias; therefore, the IPW was used to address this potential issue.

5.2 Estimation Results of the Propensity Score Matching

The PSM method first estimated the probit model of NRCMS participation, and the results are presented in Appendix Table 1. Then, using the matching method explained in Section 4.2.1, we checked whether the matching met the requirements of common support and balancing property. The solid and dashed lines in Figure 2 represent the propensity score distributions of NRCMS participants and non-participants, respectively. The overlapping area between the two lines is the common support area. A total of 120 samples were matched among the 129 non-participants, and 121 samples were matched among the 2,681 participants. The high participation rate in the NRCMS led to more unmatched cases among participants.¹⁰ In the robustness check, we confirmed that this issue did not compromise the validity of the study's conclusions. Table 4 shows a comparison of the characteristics of the two groups after matching. There were no significant differences in the mean values of all characteristics, indicating that the balancing property was satisfied. Therefore, all prerequisites for PSM were met.

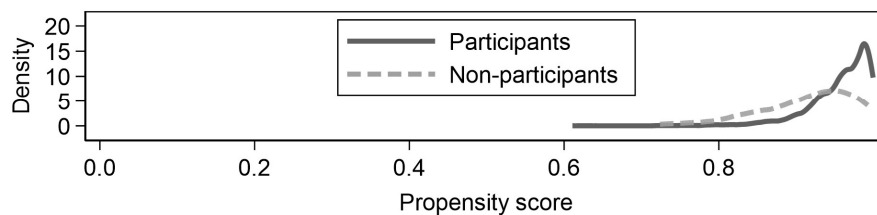


Figure 2. Common support between the participants and non-participants

¹⁰ The National People's Congress reported that the participation rate of the NRCMS in 2009 was 94%, which aligns closely with our dataset. Source: http://www.npc.gov.cn/zgrdw//npc/xinwen/jdgz/bgjy/2009-12/25/content_1532338.htm.

Table 4. Balancing property after matching.

Variable	Mean (participant)	Mean (non-participant)	<i>p</i> -value (<i>t</i> -test)
Income	22.59	19.61	0.50
Education	9.25	9.37	0.76
Age	39.83	39.86	0.98
Male	0.57	0.58	0.84
Married	0.83	0.85	0.62
Height	164.62	163.99	0.53
Weight	64.64	63.77	0.56

Note: See Appendix Table 1 for propensity score estimation. For matching, a single nearest-neighbor matching without replacement is used. 120 samples were matched among the 129 non-participants, and 121 samples were matched among the 2681 participants.

Table 5 presents the results of ATT, ATU, and ATE calculated using PSM. To ensure the robustness and accuracy of the treatment effect estimates, we employed a bootstrap method to compute the standard errors. In the ATT row, the mean represents the average daily caloric intake of the matched NRCMS participants (2,396 kcal). The counterfactual estimate of the participants' average daily caloric intake in the case of non-participation in the NRCMS was 2,067 kcal. Hence, the ATT of the NRCMS for caloric intake was 329 kcal, which was significant at the 1% level. Similarly, the ATU was 180 kcal, which was significant at the 5% level. Finally, using Equation (3), the ATE was calculated to be 255 kcal, which was significant at the 1% level.

Table 5. Estimation results of the impact of NRCMS on caloric intake by PSM.

	Mean	Counterfactual	Coefficient	Bootstrap std. err.	<i>p</i> -value
ATT	23.96	20.67	3.29	0.91	0.00***
ATU	20.70	22.49	1.80	0.81	0.03**
ATE			2.55	0.70	0.00***

Note: Bootstrap standard errors are calculated to account for sampling variability. **, *** indicating statistical significance at the 5%, 1% levels, respectively. The unit of calorie is 100 kcal. See Appendix Table 1 for propensity score estimation. For matching, single nearest-neighbor matching without replacement is used.

ATT is the Average Treatment Effect on the Treated, ATU is the Average Treatment Effect on the Untreated, and ATE is the Average Treatment Effect. The difference between the mean and the counterfactual should equal the coefficient. However, due to rounding, there may be a minor discrepancy that is not an error.

These results indicate that Hypothesis 1 (i.e., NRCMS increases calorie consumption) was supported by our dataset. This finding is highly consistent with previous studies showing that promoting health insurance increases food consumption (Hamid et al., 2011; Asfaw et al., 2022), although these studies did not specifically analyze the increase in caloric intake.

5.3 Estimation Results of the Inverse Probability Weighting Regression

To use the IPW regression, we used a logit model to predict whether individuals who participated in the 2009 survey would continue to participate in the 2011 survey (Appendix Table 2).¹¹ Table 6 presents the regression results with IPW for the log of productivity.¹² In Column (1), the base model shows that calories were significant at the 1% level, with a coefficient of 0.0133. Therefore, a 100 kcal increase in caloric intake enhanced productivity by 1.33%, supporting Hypothesis 2. Given that the sample mean of calorie was 2,300 kcal (Table 3), the estimated elasticity was approximately 0.3, which is consistent with the findings of Strauss (1986) and Kumar et al. (2015).¹³ Education was also significantly positive, consistent with previous studies (Zhang & Zou, 2007; Fan et al., 2008), but the coefficient was relatively small, with each additional year of education increasing productivity by only 1.83%. This modest effect could be attributed to two factors. First, the overall education level in rural areas is very low, averaging only the first year of junior high school. Completing one more year of education, such as moving from the first to the second year of junior high school, may not make a considerable difference for those engaged in physical labor. Second, the demand for high-skilled jobs in rural areas may be limited, reducing the returns on education. A comparison of the coefficients in Column (1) shows that an increase of approximately 138 kcal in daily caloric intake had a similar impact on productivity as an additional year of education, indicating that boosting caloric intake is a cost-efficient strategy.

Column (2) adds additional control variables, with the coefficient of caloric intake remaining stable. Age showed a significantly positive coefficient, whereas age squared was

¹¹ Income, age, marriage, and weight significantly and positively contributed to participation in the 2011 survey. This result is consistent with the design of the CHNS database. As mentioned in Section 4.1, individuals who moved to non-survey areas were not tracked. Individuals who had a higher income, were married, or were older were less likely to move. This result underscores the necessity of using weighted regression to account for varying selection probabilities.

¹² Negative productivity values (12 out of 1611) were excluded due to the log transformation. The coefficient on calorie remains significant even without the log specification, so the statistical significance reported in Table 6 does not depend on the exclusion of negative productivity values. Log transformation is standard in labor economics, as it reduces skewness and facilitates interpretation in percentage terms.

¹³ Strauss (1986) estimated an elasticity of 0.34 using data on farmers in Sierra Leone, whereas Kumar et al. (2015) found an elasticity of 0.24 for workers in India. Other studies have reported even higher elasticities; for instance, Behrman et al. (1997) estimated an elasticity of 0.61 for farmers in Pakistan, and Jha et al. (2009) reported an elasticity of approximately 0.9 for female farmers in India. The magnitude of the elasticity may be largely influenced by the degree of poverty.

significantly negative, suggesting that productivity rises with age, peaks at 39 years, and then declines, forming an inverted U-shape. This was consistent with the findings of Skirbekk (2004). Column (3) introduces the health level, and Column (4) adds productivity in 2008. Both variables slightly reduced the estimated coefficient of caloric intake; however, this remained significant, thus confirming Hypothesis 2.

Based on Columns (1)–(4), the impact of every 100 kcal increase on productivity ranged from 1.01% to 1.33%. Given that the NRCMS increased caloric intake by 255 kcal, as discussed in Section 5.1, the policy's indirect pathway may enhance labor productivity by approximately 2.58%–3.39%.

Table 6. Inverse Probability Weight Regression results explaining the log of earnings per working day.

	(1)	(2)	(3)	(4)
Calorie	0.0133*** (0.00448)	0.0127*** (0.00452)	0.0112** (0.00448)	0.0101** (0.00447)
Male	0.0164 (0.0582)	0.0287 (0.0802)	0.0422 (0.0806)	0.0383 (0.0802)
Education	0.0183** (0.00825)	0.0132 (0.00881)	0.0119 (0.00875)	0.00672 (0.00865)
Age		0.0577** (0.0257)	0.0516** (0.0258)	0.0521** (0.0262)
Age Squared		-0.000746** (0.000304)	-0.000666** (0.000305)	-0.000691** (0.000308)
Married		-0.165 (0.110)	-0.132 (0.110)	-0.191* (0.104)
Height		0.00233 (0.00540)	0.00182 (0.00543)	0.00170 (0.00544)
Weight		-0.00342 (0.00335)	-0.00329 (0.00337)	-0.00455 (0.00337)
Sick Days			-0.0278 (0.0191)	-0.0284 (0.0186)
Productivity_2008				0.00131*** (0.000443)
Region dummy	√	√	√	√
n	1599	1599	1578	1553

Note: The numbers in parentheses represent the standard errors. *, **, *** indicating statistical significance at the 10%, 5%, 1% levels, respectively. See Appendix Table 2 for the computation of inverse probability weights.

6. Robustness Test

6.1 Robustness Test Results for Hypothesis 1

One implicit assumption of PSM (our method for Hypothesis 1) was that when all covariates **X** used to predict NRCMS participation were balanced, the probability of participation would be equal for all individuals. However, in the presence of unobserved covariates that affect treatment assignment, this assumption may not hold. The Rosenbaum robustness test evaluates the sensitivity of the PSM results to potential unobserved covariates (Rosenbaum, 2002). It introduces a gamma parameter to simulate the possible impact of unobserved covariates on the propensity scores. If the results remain significant

at higher gamma values, the PSM estimates are more robust. A gamma value of 2 indicates absolute insensitivity to hidden bias, values between 1.5 and 2 indicate relative robustness, and values below 1.5 suggest a lack of robustness (Xu et al., 2024).

Appendix Table 3 presents the Rosenbaum robustness test results. When gamma reached 1.7, the results remained significant at the 5% level; when gamma reached 1.9, the results remained significant at the 10% level. Therefore, the validation of Hypothesis 1 using PSM in this study was relatively robust.

Another robustness check for Hypothesis 1 was IPW, which controls for confounding variables by weighting observations based on the inverse of propensity scores (Lunceford & Davidian, 2004). Unlike PSM, which evaluates only matched samples and may introduce bias by ignoring unmatched samples, IPW includes all samples by weighting them to balance the covariates between the treatment and control groups. Table 4 in the Appendix presents these results. The ATE of the NRCMS for caloric intake was 286 kcal, which was significant at the 1% level. This is closely aligned with and even slightly exceeds the PSM estimate, indicating robustness.

6.2 Robustness Test Results for Hypothesis 2

To evaluate the appropriateness of using a linear model to test Hypothesis 2, we applied a nonparametric kernel regression to verify the contribution of calories to productivity and compared it with the original linear estimates (Rios-Avila, 2020). It was also used as a robustness check by Farrukh et al. (2023).

Appendix Table 5 presents the nonparametric kernel regression results for the average marginal effect of calories on the log of productivity. A 100 kcal increase in caloric intake raised productivity by approximately 1.5%, which was significant at the 1% level. This estimate is close to and slightly higher than the result in Section 5.3, suggesting that the original linear specification was robust.

7. Conclusion

This study investigated an indirect pathway through which the NRCMS impacts human capital by increasing calorie consumption to enhance labor productivity. Given that the role of caloric intake as a form of human capital has been validated in other developing

countries (Jha et al., 2009; Schilbach et al., 2016), we believe that the indirect pathway through health insurance subsidies offers valuable insights. Therefore, a promising avenue for future research is to empirically validate this mechanism using data from regions such as Sub-Saharan Africa and South Asia.

A limitation of this study was that its findings were primarily derived from contexts in which income levels are extremely low and physical labor constitutes the dominant form of occupation. As such, the observed effects may not be generalizable beyond these settings, particularly in countries graduating from a low-income status and developed countries (Dall et al., 2009). Therefore, further case studies under diverse settings are required.

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Appendix

Appendix Table 1 presents the regression results from the probit model, with participation in the NRCMS (participant = 1, non-participant = 0) as the dependent variable and a set of individual characteristics as the independent variables. A PSM analysis can be conducted by determining the probability of rural population participation in the NRCMS.

Appendix Table 1. Results of probit model explaining the participation into the NRCMS program.

Variables	Coefficient on NRCMS participation
Income	-0.00183 (0.00129)
Education	-0.124*** (0.0168)
Age	0.00528 (0.00483)
Male	0.157 (0.129)
Married	0.219 (0.140)
Height	-0.00265 (0.00931)
Weight	-0.0129*** (0.00498)
Region dummy	Yes
Pseudo R2	0.106
n	2810

Note: The numbers in parentheses represent the standard errors. *** indicating statistical significance at the 5%, 1% levels, respectively.

Appendix Table 2 presents the results of using a logit model to predict whether individuals who participated in the 2009 survey would continue participating in the 2011 survey. The dependent variable was continued participation (1 for participation in both 2011 and 2009, and 0 for participation in 2009 only), and the independent variables were a set of individual characteristics. Based on the logit results, weights w_i can be calculated for each sample i .

Appendix Table 2. Logistic regression results for predicting survey participation.

Variables	Coefficient on 2011 participation
Income	0.00319* (0.00178)
Education	-0.0108 (0.0131)
Age	0.00739* (0.00416)
Male	0.00679 (0.110)
Married	0.973*** (0.138)
Height	-0.0105 (0.00787)
Weight	0.00814* (0.00454)
Region dummy	Yes
Pseudo R^2	0.0403
n	2,947

Note: The numbers in parentheses represent the standard errors. *, *** indicating statistical significance at the 10%, 1% levels, respectively.

Appendix Table 3 presents the Rosenbaum robustness test results. Sig+ represents the significance level assuming that unobserved confounders increased the likelihood of being in the treatment group, whereas Sig- represents the significance level assuming that unobserved confounders increased the likelihood of being in the control group. When gamma reached 1.9, both Sig+ and Sig- remained significant, indicating that the PSM results were relatively robust to potential unobserved confounders.

Appendix Table 3. Results of the Rosenbaum robustness test.

Gamma	sig+	sig-
1	0.000012	0.000012
1.1	0.000079	1.4e-06
1.2	0.00037	1.6e-07
1.3	0.001313	1.7e-08
1.4	0.003745	1.8e-09
1.5	0.00898	1.9e-10
1.6	0.018713	1.9e-11
1.7	0.034761	2.0e-12
1.8	0.058712	2.0e-13
1.9	0.091592	2.0e-14
2	0.133652	1.9e-15

Note: Sig+ and Sig- represent upper and lower bounds significance level, respectively.

Appendix Table 4 presents the estimation results using IPW.

Appendix Table 4. Estimation results of the impact of NRCMS on caloric intake by IPW.

Coefficient	Robust std. err.	P-value
2.86	0.55	0.00***

Note: *** indicating statistical significance at the 1% levels.

Appendix Table 5 presents the results of a nonparametric kernel regression to estimate the effect of calories on productivity. This method did not require the specification of a functional form for the model but relied on data to define the relationship between the independent variable (calories) and the dependent variable (log of productivity). This approach allowed us to capture the complex and nonlinear relationships between calories and productivity without the constraints of a predetermined model.

Appendix Table 5. Estimation results of the effect of calories on log of productivity using nonparametric kernel regression.

Effect	Bootstrap std. err.	z	P> z
0.015	0.004	3.46	0.001***

Note: *** indicates statistical significance at the 1% levels.