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The long-term impact of the nutrition improvement program on children's education outcomes: Empirical evidence from rural China

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ABSTRACT

Existing research on nutritional assistance largely focuses on its short-term effects. Using data from the 2019 China Household Finance Survey (CHFS), this research investigates the long-term effects, underlying mechanisms, and cost-effectiveness of the Nutrition Improvement Program (NIP), a widespread school meal program in rural China, on students' educational attainment. Our findings indicate that the NIP significantly increases the likelihood of students attending high school and college and extends their years of education. These results are robust across various sensitivity tests. The NIP improves educational attainment by enhancing students' health, cognitive abilities, non-cognitive skills, and parental educational expectations. Furthermore, the impact is more pronounced among students with lower parental education levels and those in western regions. A cost-benefit analysis shows that the economic returns of the NIP surpass its costs, highlighting its substantial economic efficiency. This research underscores the importance of school meal programs as a human capital investment and provides valuable insights for policymakers in China and other developing nations seeking to address educational inequality and improve population health and well-being.

1. Introduction

China, one of the world's largest developing countries, has achieved remarkable progress in poverty alleviation and economic growth. Particularly noteworthy is China's success in poverty alleviation, which can be regarded as a miracle in the history of humanity's fight against poverty. In this campaign, nutritional improvement, especially interventions targeting children, has been viewed as a critical link in breaking the intergenerational cycle of poverty and effectively preventing relapse into poverty. For a long time, China has faced significant disparities in nutritional status between urban and rural areas, with rural children experiencing notable gaps in nutritional intake compared to their urban counterparts. As the national economy has developed and living standards have improved, the basic living goals of "no worries about food and clothing" have gradually been realized. However, the shift from "having enough to eat" to "eating well," particularly in rural areas, has become a new challenge of the era. In response, the Chinese government has demonstrated a high sense of responsibility and foresight by promptly launching the "Nutrition Improvement Program for Rural Students (NIP)". The implementation of this program not only provides strong support for rural education in China, promoting educational equity and social justice, but also offers valuable references and lessons for other countries facing similar issues of unequal resource allocation between urban and rural areas. Globally, especially in many developing countries, child malnutrition remains a severe problem that constrains social and economic development. The experience and achievements gained from China's implementation of the NIP undoubtedly provide a replicable and adaptable model for these countries.

China's aging population and slowing economic growth necessitate a focus on enhancing labor force quality. Human capital theory positions education as the key driver for building a skilled workforce, thereby boosting productivity and economic well-being (Becker, 1962; Lucas, 1988). The Chinese government has consistently prioritized education advancement through long-standing policies such as universal

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compulsory education (since 1986) and college enrollment expansion (since 1999). These initiatives have demonstrably improved population quality and fueled economic growth (Li et al., 2017). However, a significant disparity in educational resources persists between urban and rural areas, with China lagging behind developed nations in overall educational attainment (Luo and Hu, 2024). Bridging this urban-rural gap is essential for rural revitalization and achieving shared prosperity. Therefore, bolstering investment in and support for rural education takes on heightened significance.

The educational disparity between urban and rural China extends beyond infrastructure and teacher resources. It manifests most acutely in students' nutritional support. Urban students generally have better access to a balanced diet, whereas their rural counterparts face more challenging circumstances. Data from the Chinese Center for Disease Control and Prevention in 2012 paint a troubling picture: nearly half of rural primary and middle school students lacked guaranteed daily meals, and their diets were often monotonous, lacking essential nutrients like meat, eggs, and dairy products. These long-term deficiencies can harm children's physical health, weaken cognitive abilities, affect academic performance, and potentially diminish their future human capital and income level (Currie, 2009). While the poorer economic conditions in rural areas contribute to this problem, a significant factor is the lack of emphasis on providing scientifically balanced nutrition for children by parents in these regions. This underscores the crucial role of government nutritional assistance in bridging this gap.

The Chinese central government launched the NIP in 2011 to address the nutritional disparities and promote balanced urban-rural education development. The NIP primarily provides nutritional assistance to rural compulsory education students through government subsidies and school meal programs. Initially, a pilot program was rolled out in 699 designated counties (national pilot counties) with a daily lunch subsidy of 3 yuan per student, increasing to 5 yuan by 2021. Some local governments launched similar initiatives in specific counties (local pilot counties) with the potential for incentive funding upon meeting certain criteria. Data from the China National Center for Student Financial Aid in 2022 show the NIP has extensive coverage across 28 provinces, benefiting over 35 million students. Given its broad reach, substantial funding, and long-term implementation, a thorough evaluation of the NIP's effectiveness, both theoretically and practically, is crucial.

Apart from China, many countries have also enacted nutrition improvement programs. The body of research examining the impacts of nutritional support is vast and substantial. The first wave of these studies examined its impact on students' physical development and health, often reporting positive outcomes (Afridi, 2010; Gundersen et al., 2012; Gelli et al., 2019). However, some studies suggested these nutritional programs may increase obesity risk (Schanzenbach, 2009) or have minimal health benefits (Buttenheim et al., 2011). The second wave of studies explored the impact on short-term academic performance. While some studies found that these programs improve academic achievement and enrollment rates (Belot and James, 2011; Frisvold, 2015), other studies indicated that the effect is not significant or ineffective (McEwan, 2013; Imberman and Kugler, 2014). Some literature has examined the long-term effects. For example, Hinrichs (2010) found the 1960s US school meal program significantly boosted students' long-term educational attainment. Similarly, Lundborg et al. (2022) observed a substantial increase in long-term educational attainment for students who participated in Sweden's free lunch program (1959–1969).

As the NIP advances, some studies have begun to explore its broad economic implications. Short-term research has focused on immediate effects such as student test scores, maternal labor participation, and household investment in children's education (Wang et al., 2024; Duan et al., 2024; Wang & Cheng, 2022). Longitudinally, the scope extends to the program's profound impacts on cognitive abilities, health status, and future employment probabilities (Liang et al., 2024; Fang and Zhu, 2022; Zhou et al., 2024). Despite this wide-ranging research, there remains a gap in understanding how the NIP specifically influences long-term educational attainment. Although Liang et al. (2024) touch upon this topic, their analysis based on data from 2015 may not fully capture changes in post-secondary education, potentially leading to underestimation of policy effects. To address this, our study extends the timeframe to 2019, thereby complementing existing research.

In terms of research design, previous studies often overlook the non-random selection of pilot counties (Zhou et al., 2024; Wang et al., 2024). Pilot counties are predominantly impoverished areas that benefit from multiple policy interventions, including vocational high school financial aid and increased university admission quotas. Failure to account for these additional policies could lead to overestimated effects in the studies. Our approach mitigates this bias by controlling for the prerequisites of pilot county selection, the influence of free vocational education, and targeted university enrollment plans.

Furthermore, much of the existing literature emphasizes the economic benefits of the NIP but rarely compares them with associated costs (Liang et al., 2024; Fang and Zhu, 2022). This study innovatively integrates a cost-benefit analysis framework, evaluating not only the direct economic impact of policy implementation but also scrutinizing the allocation efficiency of resources. This comprehensive approach provides richer and more diverse evidence supporting the economic value and social impact of China's NIP.

To address the limitations of existing research, this paper delves into the potential benefits of the NIP. By employing the Cohort Difference in Differences (DID) identification strategy, this paper aims to evaluate the NIP's impact on students' long-term educational attainment, its underlying mechanisms, and potential variations across different regions and households. Furthermore, to gain a comprehensive understanding of the NIP's economic value, this paper supplements prior studies by assessing its income effects and conducting a cost-benefit analysis. This deeper exploration will not only inform refinements to the NIP but also illuminate its potential to narrow the urban-rural education gap and contribute to inclusive prosperity.

This paper makes three key contributions to existing literature. First, it expands the scope of research on nutritional assistance. Existing literature on the long-term educational impacts of China's NIP remains inadequate. While Liang et al. (2024) have conducted relevant research, the educational tracking period in that study is relatively short, which may lead to an underestimation of the policy effects. In contrast to Liang et al. (2024), our study examines the impact over a longer educational horizon, thereby further extending the boundaries of the NIP effect research. By doing so, this research enhances our understanding of how school meal programs contribute to long-term human capital accumulation and provides theoretical support for further program refinements.

Second, our study addresses the non-random allocation of pilot counties and excludes the interference from other policies. By doing so, we mitigate, to some extent, the common issue of policy effect bias prevalent in such research.

Third, it conducts a cost-benefit analysis of the NIP, offering a more comprehensive picture of its economic value. While Chinese government agencies perform evaluations of fiscal policies, these often focus on short-term performance and fund utilization. This paper's cost-benefit analysis, based on the NIP's long-term income effects, helps assess the economic rationality of the program and informs the optimization of fiscal resource allocation for long-term human capital development.

2. Policy background and theoretical analysis

2.1. Policy background

For decades, the nutritional well-being of rural students in impoverished areas of China has been a pressing social concern. Economic constraints and a lack of parental emphasis on health issues often lead to these students experiencing nutritional deficiencies (Popkin, 2008). These deficiencies not only pose a direct threat to their physical health but also hinder efforts to achieve educational equity. Since the turn of the 21st century, social organizations and groups have launched localized initiatives such as the Free Nutritious Breakfast Project and the Public Welfare Free Lunch Program to address this issue. However, these programs struggle to meet the vast and urgent nutritional needs of the majority of rural students in China due to limited funding and coverage.

To address the nutritional deficiencies of rural students, particularly in impoverished areas, the Chinese government launched the NIP in 2011. The program's initial phase involved designating 699 counties as national pilot counties. In these counties, students received daily nutritional subsidies of 3 yuan through a combination of central financial assistance and standardized school meals. The central government further encouraged localized trials in 616 additional counties (local pilot counties). Funding for these trials primarily came from local sources, with the central government offering incentive funding based on their effectiveness. Recognizing the importance of infrastructure, a special fund of 30 billion yuan was allocated for school cafeteria construction to facilitate smooth program implementation. The NIP has seen continuous expansion since its inception. Coverage has broadened to encompass all previous poverty counties, and the subsidy standard for national pilot counties has grown from 3 yuan per student per day to 5 yuan by 2021.

The primary differences in policy implementation between national pilot counties and local pilot counties are as follows. Geographically, national pilot counties are predominantly located in China's contiguous impoverished regions, where economic development levels are typically lower, and student nutrition conditions urgently require improvement. In contrast, local pilot counties may include ethnic minority counties, border counties, old revolutionary base counties, and relatively affluent counties, which can exhibit varying levels of economic development and nutritional status. In terms of policy support, national pilot counties benefit from direct policy support and financial subsidies provided by the central government, ensuring the smooth implementation of the NIP. For local pilot counties, policy support and financial subsidies are often jointly borne by both local and central governments, with the specific sharing ratio varying by region. Regarding implementation standards, national pilot counties adhere to uniform standards and requirements set by the central government for the NIP, encompassing aspects such as meal provision, subsidy levels, and food safety. Local pilot counties, while still needing to meet the basic requirements set by the central government, may make appropriate adjustments based on local conditions when implementing the NIP.

The Chinese government implemented several measures to ensure the NIP's effective execution. In February 2012, the Ministry of Education established a dedicated leadership group, headed by the Minister of Education himself. The Ministry of Finance concurrently issued regulations for managing cafeteria construction and special funds. Additionally, the State Council Education Supervision Committee coordinated resources, oversaw food and financial safety, and ensured subsidies reached their intended purpose — improving student nutrition. These combined efforts led to a gradual improvement in the NIP's regulatory framework, laying a solid foundation for the program's long-term success.

Years of implementing the NIP have yielded significant results. By 2021, the central government had invested over 196.7 billion yuan, benefiting an average of 37.95 million students annually. The program has demonstrably improved the health of rural students, particularly in impoverished areas, as evidenced by their enhanced physical fitness and a marked decline in malnutrition rates. Beyond health improvements, the NIP has also lightened the financial burden on low-income families, potentially alleviating intergenerational poverty transmission.

2.2. Theoretical analysis

A person's educational attainment is shaped by two key factors: their own learning efficiency and their parents' expectations for their education (Fang et al., 2018). Those who learn efficiently and have parents who encourage higher education typically achieve better educational outcomes. This paper proposes that nutritional support can significantly improve educational attainment by enhancing both learning efficiency and parental expectations.

First, let's explore how nutritional support enhances learning efficiency. By improving students' health, nutritional support lays the groundwork for better learning outcomes. When students are healthy, their brains function with sharper focus and increased attentiveness, leading to improved comprehension and retention of information. Conversely, poor health or inadequate nutrition can hinder concentration and pose cognitive challenges (Behrman and Rosenzweig, 2004). Research in rural China highlights the prevalence of malnutrition among students, underscoring the critical role of nutritional support in meeting their dietary needs and ultimately enhancing their learning outcomes (Gundersen et al., 2012; Chakraborty and Jayaraman, 2019; Fang and Zhu, 2022). Furthermore, nutritional support significantly contributes to enhancing both cognitive and non-cognitive abilities, thereby refining learning efficiency. Studies suggest that it not only sharpens cognitive skills such as attention, memory, and processing speed, but also nurtures non-cognitive aspects like emotional regulation and social aptitude (Frisvold, 2015; Zheng et al., 2023). Strong cognitive abilities facilitate quicker comprehension and mastery of new concepts, while robust non-cognitive skills foster a positive mindset and resilience, both critical for optimizing learning efficiency (Currie, 2009).

Next, let's explore how parental expectations influence their children's educational achievement. Parents typically shape their aspirations for their children's education by carefully considering the investment required and the potential returns. When a policy effectively reduces the costs or enhances the benefits of education for children, it naturally raises parents' expectations. Nutritional support primarily bolsters parental expectations by alleviating the costs associated with education in two main ways: First, by easing the financial strain of food expenses on families and reducing the time spent on meal preparation, it directly lowers the financial costs of education (Gertler, 2004). Second, the improvement in children's health, cognitive abilities, and non-cognitive skills resulting from nutritional support contributes to enhancing the educational returns per unit of parental investment. When parents anticipate these improvements, they are more likely to make decisions that facilitate their children's educational advancement, such as investing more time and financial resources, and even considering relocating for better educational opportunities. As a result, parental expectations are raised, fostering an increase in their children's educational achievement (Yamamoto and Holloway, 2010).

Based on the preceding analysis, we propose the following hypotheses:

H1. Nutritional assistance contributes to enhancing individuals' educational attainment.

H2. Nutritional assistance boosts individuals' educational attainment by improving their health status, cognitive abilities, non-cognitive skills, and parental expectations.

3. Identifying strategies, models, and data

3.1. Identifying strategies

Cohort Difference-in-differences (Cohort DID), proposed by Duflo (2001), is a widely used method in policy evaluation. Cohort DID analysis involves examining changes along two dimensions: the difference before and after policy implementation (identified by age group), and the difference between regions affected by the policy and those unaffected. Each dimension is explained separately below.

3.1.1. Age group setting

The NIP was implemented in 2011, primarily benefiting rural students in pilot areas who were in the compulsory education stage. Therefore, the maximum age group affected by the policy was students in ninth grade in 2011. According to the age requirement of 6 years old for children to enter school in China, children typically attend ninth grade at the age of 15. Therefore, in 2011, individuals aged 15 or younger were affected by the NIP, while those older than 15 were not affected. Additionally, to ensure that all study subjects were above the age for college enrollment in the survey year (2019), this paper chose to set the youngest age group as individuals who were 12 years old in 2011 (i.e., in sixth grade). The age group setting is as follows:

$$post_t = \begin{cases} 1, & if\ 12 \leq age_i \leq 15 \\ 0, & if\ 16 \leq age_i \leq 19 \end{cases} \quad (1)$$

In formula (1), age_i represents the age of the individual i in 2011, and $post_t$ denotes whether the individual was in the compulsory education stage after the policy implementation.

3.1.2. Regional policy disparities

With rural students in pilot areas during compulsory education being the primary beneficiaries of the NIP, this study focuses solely on rural students. Pilot areas include both national and local pilot counties. Recognizing significant variations in policy implementation timing and intensity among local pilot counties, this study primarily investigates the policy's effects in national pilot counties. Consequently, local pilot counties are not included in the baseline regression analysis. Rural students in national pilot counties are designated as the treatment group, while those in other regions serve as the control group.

3.2. Model specification

Based on the age group setting and regional policy disparities, we establish a Cohort DID model to investigate the impact of the NIP on individuals' educational attainment. Drawing from Chen et al. (2020), the baseline regression model is specified as follows:

$$Y_{ict} = \alpha_0 + \alpha_1 treat_c \times post_t + \omega X_{ict} + \gamma_t + \delta_c + \varepsilon_{ict} \quad (2)$$

In equation (2), Y_{ict} represents the educational attainment of the individual; $treat_c$ denotes whether the individual is in a national pilot area for the NIP; $post_t$ is defined similarly to equation (1); X_{ict} is a vector of control variables; γ_t represents age group fixed effects; δ_c represents county fixed effects; and ε_{ict} is the random error term. Under the assumption of parallel trends, α_1 reflects the causal impact of the NIP on individuals' educational attainment.

The parallel trends assumption suggests that if pilot areas had not implemented the program, the educational attainment of their population would have followed a trajectory similar to that of other areas. However, the educational attainment of the population in pilot areas cannot be observed in the absence of the NIP. Therefore, following Duflo (2001), this study conducts a parallel trend test by examining whether the NIP affected the educational attainment of individuals who had completed compulsory education at the time of policy implementation. Specifically, individuals aged 19 in 2011 are considered the control group, while those aged 16–18 are considered the treatment group. If it is found that the program did not significantly impact the educational attainment of individuals who had completed compulsory education at the time of policy implementation, this would indicate that the assumption of parallel trends before the policy was implemented holds true.

3.3. Data

The study draws upon data from three primary sources. Firstly, the baseline regression data is extracted from the 2019 China Household Finance Survey (CHFS), conducted by the Survey and Research Center for China Household Finance of Southwestern University of Finance and Economics since 2011. This nationwide survey covers 29 provinces in China, including autonomous regions and municipalities directly under the central government. It provides essential information such as individual characteristics, family background, and economic status. The samples are categorized into national pilot counties (678), local pilot counties (533), and non-pilot counties (1206) by aligning county codes with those of the NIP's pilot counties. Since the study focuses on the policy effects of national pilot counties, samples from local pilot counties are excluded from the baseline regression. Additionally, only samples with rural household registrations are retained in the baseline regression, as the NIP primarily targets students in rural compulsory education. After removing missing values and outliers, a total of 4090 valid samples are obtained.

Secondly, county-level data used for Propensity Score Matching-Difference in Difference (PSM-DID) estimation is sourced from the China Statistical Yearbook (County-Level) (CSYCL) in 2011.[2] This dataset provides comprehensive economic and social development information for county-level administrative units in China, covering aspects such as population distribution, economic development, and financial status. After rigorous data cleaning procedures to eliminate outliers and missing values, a total of 1120 valid samples are retained for analysis. Additionally, the control variables include data extracted from the CSYCL for the 2007–2009 period, specifically per capita GDP, per capita general public budget revenue, and per capita disposable income of rural residents.

Thirdly, data for mechanism analysis is obtained from the China Education Panel Survey (CEPS) baseline and tracking data. The baseline survey collected essential information such as personal characteristics, family background, and school conditions of seventh and ninth-grade students. Subsequently, a tracking survey was conducted on the original seventh-grade students the following year. The baseline and tracking data are matched to obtain panel data for students in seventh and eighth grades, facilitating the mechanism analysis. Given the NIP's primary focus on rural students, only samples from rural backgrounds are retained for this analysis. After careful removal of missing values and outliers, a total of 1942 valid samples are obtained.

3.4. Variables

3.4.1. Dependent variable

Education Level. This study delineates individuals' education levels based on three key aspects: high school or above, college or above, and years of education. The transformation method for years of education is as follows: categories of no education, primary school, junior high school, high school (or vocational school), junior college (or technical school), college, master's, and doctoral degrees are mapped to 0, 6, 9, 12, 15, 16, 19, and 23 years, respectively.

3.4.2. Core explanatory variable

Receipt of Assistance from the NIP. As previously stated, this study determines whether individuals have received assistance from the NIP based on their age and geographical location. Individuals who resided in pilot areas for the NIP and were within the compulsory education stage following the policy implementation are categorized as having received assistance; otherwise, they are categorized as not having received assistance.

3.4.3. Control variables

This study includes the following basic control variables: gender, ethnicity, family size, father's years of education, and mother's years of education. Importantly, we control for the prerequisites of national pilot county selection. Since national pilot counties are designated as poor counties, including a dummy variable for poor counties would cause perfect multicollinearity. Following Li et al. (2016), we use alternative criteria for controlling poverty county status. Based on policy

[2] In subsequent robustness tests, the PSM-DID method was employed.

documents,[3] the designation of poor counties relies on indicators such as per capita GDP, per capita general public budget revenue, and per capita rural net income from 2007–2009. Therefore, we included interaction terms of county-level per capita GDP, per capita general public budget revenue, and per capita disposable income of rural residents with years relative to the pilot time in our baseline model. Additionally, in subsequent robustness tests aimed at mitigating potential policy interference effects, controls are incorporated for expanded enrollment in college education, school merger and closure, free vocational education policy, and college targeted enrollment program. Furthermore, to address heterogeneity differences between treatment and control groups in subsequent PSM-DID estimation, county-level variables such as population density, urbanization rate, tertiary sector share, per capita GDP, per capita fiscal expenditure, and student-teacher ratio are balanced.

3.4.4. *Mechanism variables*

As mentioned earlier, this study scrutinizes how the NIP influences individuals' education levels from four dimensions: health status, cognitive ability, non-cognitive ability, and parental education expectations. Firstly, in alignment with Zheng et al. (2023), we assess the non-cognitive abilities of seventh and eighth-grade students through specific questions. These questions evaluate statements such as "I can clearly express my opinions", "I react very quickly", "I can quickly learn new knowledge", and "I am very curious about new things". Responses range from 1 (completely disagree) to 4 (completely agree), and their averages are computed as proxy variables for non-cognitive abilities. Secondly, following Gong et al. (2018), variables including health status, cognitive ability, and non-cognitive ability are standardized by grade in the regression analysis. This standardization adjusts these variables to have a mean of 0 and a standard deviation of 1.

The descriptive statistics of the variables are shown in Table 1.

Table 1
Descriptive statistics.

Variable	Definition	Mean	SD
	CHFS		
NIP	Individual is in a national pilot area of the NIP (yes = 1, no = 0)	0.215	0.411
High school or above	Individual has completed at least high school education (yes = 1, no = 0)	0.628	0.483
College or above	Individual has completed at least college education (yes = 1, no = 0)	0.432	0.495
Education years	Individual's years of education	12.236	3.612
Income	Individual's wage income (in ten thousand yuan)	3.642	2.375
Man	Individual is male (yes = 1, no = 0)	0.662	0.473
Age	Individual's age	25.071	3.457
Minority	Individual belongs to an ethnic minority (yes = 1, no = 0)	0.133	0.340
Family size	Total population of the individual's family (persons)	4.656	1.457
Father education	Years of education for the individual's father	8.123	2.897
Mother education	Years of education for the individual's mother	6.648	3.362
	CSYCL averge from 2007 to 2009		
Per capita GDP	GDP per capita (in ten thousand yuan)	2.281	2.829
Per capita public revenue	General public budget revenue per capita (in ten thousand yuan)	0.182	0.752
Per capita rural income	Disposable income of rural residents per capita (in ten thousand yuan)	0.573	0.421
	CSYCL in 2011		
Population density	Population density (ten thousand persons per square kilometer)	0.081	0.243
Urbanization rate	Proportion of urban permanent residents to total permanent residents (%)	28.458	20.990
Tertiary sector share	Share of tertiary industry output in GDP (%)	32.359	11.603
Per capita GDP	GDP per capita (in ten thousand yuan)	2.831	2.465
Per capita fiscal expenditure	Fiscal expenditure per capita (in ten thousand yuan)	0.335	0.352
Student-teacher ratio	Ratio of elementary school students to teachers	17.636	7.597
	CEPS		
Health status	Self-rated health, rated from 1 to 5 indicating from very unhealthy to very healthy	4.038	0.905
Cognitive ability	Standardized scores from cognitive ability tests	0.580	0.218
Non-cognitive ability	Non-cognitive abilities, calculated based on a series of specific questions	3.136	0.590
Parental education expectations	Highest level of education that student' parents expect them to achieve	16.196	3.005
Eighth grade	Student is in eighth grade (yes = 1, no = 0)	0.521	0.500
Nutritional assistance	Student's school provides free lunch (yes = 1, no = 0)	0.131	0.338
Male	Student is male (yes = 1, no = 0)	0.516	0.500
Age	Student's age	13.135	0.911
Minority	Student belongs to an ethnic minority (yes = 1, no = 0)	0.159	0.365
Father education	Years of education for student's father	9.396	2.351
Mother education	Years of education for student's mother	8.547	3.012
Economic status	Family economic status of student, rated from 1 to 5 indicating from very difficult to very affluent	3.071	0.541

4. Empirical results

4.1. *Effects of the NIP*

The estimated impact of the NIP on educational attainment is presented in Table 2. Models (1), (3), and (5) control for age group and county fixed effects, while models (2), (4), and (6) further account for individual characteristics such as gender, ethnicity, family size, and parental education, and the prerequisites of national pilot county selection. The results reveal a significant positive effect of the NIP. Individuals are 12.9% more likely to attend high school and 13.3% more likely to attend college following the program's implementation. Additionally, their average years of education increased by 1.00 years. These findings support our hypothesis (H1).

Importantly, China's urban residents tend to have higher educational attainment than rural residents. Since the NIP primarily benefits rural students, this study suggests the program plays a crucial role in promoting educational equity and narrowing the urban-rural education gap.

4.2. *Parallel trends test*

The effectiveness of the DID strategy in isolating the causal effect of the NIP on educational attainment hinges on the parallel trends assumption.

This section verifies this assumption by examining the NIP's impact on a group that had already completed compulsory education by the policy's implementation year (individuals aged 16–18 in 2011), as shown in Fig. 1. The lack of a significant NIP effect on their years of education suggests parallel trends between the treatment and control groups prior to the policy. This finding strengthens the validity of the DID approach.

4.3. *Robustness Test*

4.3.1. *Accounting for late enrollment and grade retention*

The analysis assumes strict adherence to the standard school entry age of 6 and no grade repetition during compulsory education. However, late enrollment and grade retention can occur, potentially introducing measurement errors in pre- and post-policy comparisons. For example, some individuals exceeding 15 years old in 2011 might be affected by

[3] https://www.gov.cn/gzdt/2012-06/14/content_2161045.htm.

Table 2
Effects of the NIP on individual educational attainment.

	High school or above		College or above		Education years	
	(1)	(2)	(3)	(4)	(5)	(6)
NIP × Post	0.096**	0.129**	0.088**	0.133***	0.764***	1.003***
	(0.038)	(0.054)	(0.043)	(0.050)	(0.294)	(0.378)
Individual characteristics	No	Yes	No	Yes	No	Yes
Selection criteria for pilots × T	No	Yes	No	Yes	No	Yes
Selection criteria for pilots × T^2	No	Yes	No	Yes	No	Yes
Selection criteria for pilots × T^3	No	Yes	No	Yes	No	Yes
Age group effects	Yes	Yes	Yes	Yes	Yes	Yes
County effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2768	2768	2768	2768	2768	2768
R^2	0.184	0.263	0.156	0.235	0.208	0.304

Note(s): 1. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively. 2. Robust standard errors clustered at the district level are shown in parentheses. 3. Selection criteria for pilots include per capita GDP, per capita general public budget revenue, and per capita disposable income of rural residents.

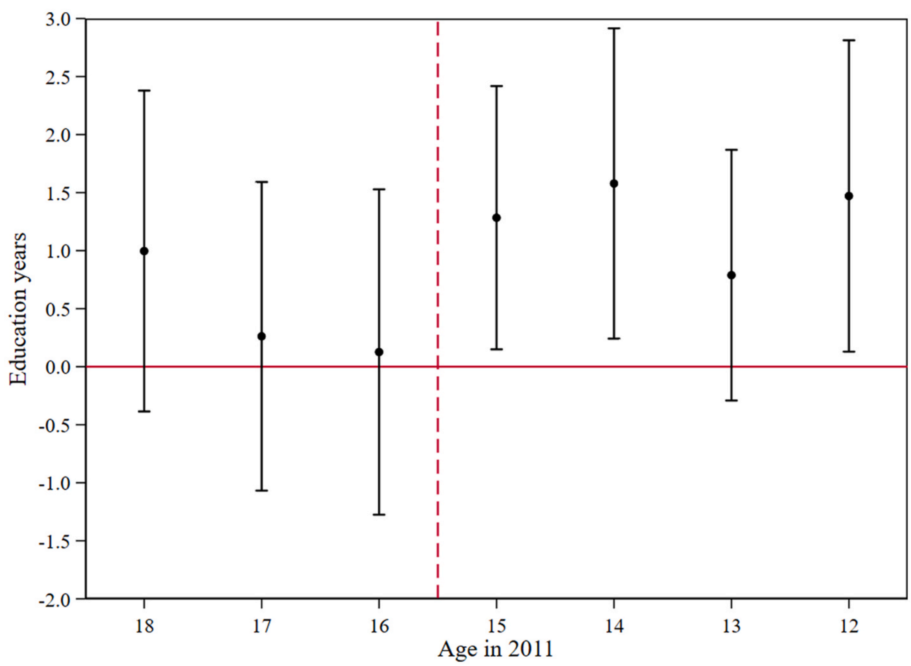

Fig. 1. Results of the parallel trends test.

the NIP but categorized as unaffected. Similarly, some young individuals might not reach college age by 2019, leading to inaccuracies in measuring educational attainment. To address these concerns, we exclude individuals from the 12- and 16-year-old age groups in 2011. The results in Table 3, Column (1), show highly similar coefficient estimates to the baseline regression. This indicates that our conclusions remain robust after accounting for late enrollment and grade retention.

4.3.2. *Mitigating the impact of population mobility*

Mobile populations may have received compulsory education elsewhere while working locally. If the NIP implementation differs between these regions, this could lead to misclassification of treatment and control groups, potentially underestimating the policy effect. To address this, we restrict the sample to individuals whose current residence matches their registered household residence, thereby excluding the impact of population mobility. Table 3, Column (2), shows that the program's positive effect on educational attainment persists even after accounting for this factor.

4.3.3. *Refining the control group with PSM-DID*

To mitigate potential heterogeneity between treatment and control groups, we employ PSM-DID. First, we estimate a 1:1 nearest neighbor

Table 3
Results of the robustness test.

	Explained variable: years of education			
	Excluding the impact of late enrollment and grade retention (1)	Excluding the impact of population mobility (2)	PSM-DID (3)	Placebo test: using non-rural samples (4)
NIP × Post	0.844*	1.375***	1.204**	0.115
	(0.461)	(0.415)	(0.584)	(0.415)
Control Variables	Yes	Yes	Yes	Yes
Age group effects	Yes	Yes	Yes	Yes
County effects	Yes	Yes	Yes	Yes
Observations	1981	1955	733	1500
R^2	0.318	0.375	0.318	0.388

Notes: 1. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively. 2. Robust standard errors clustered at the district level are shown in parentheses.

PSM-DID model using 2010 county-level data. The dependent variable is whether a county is a pilot area for the program, and the independent variables include population density, urbanization rate, share of the tertiary industry, per capita GDP, per capita fiscal expenditure, and student-teacher ratio. The matched district samples are then linked to the individual-level CHFS data, and Equation (2) is re-estimated. Table 3, Column (3), shows that our conclusions remain consistent even after applying PSM-DID.

4.3.4. Placebo test: using non-rural samples

The NIP primarily targets rural students in pilot areas during compulsory education. Theoretically, the program should not significantly impact the educational attainment of non-rural students. To validate this assumption, we re-estimate Equation (2) using the sample of individuals with non-rural household registration. Table 3, Column (4), shows that the interaction term coefficient becomes insignificant. This supports the validity of our initial assumption and the effectiveness of the DID identification strategy.

4.3.5. Accounting for potential policy interference

The benchmark regression results might be influenced by other government initiatives that affect student educational attainment.

First, addressing the impact of college expansion. Since the late 1990s, China has steadily expanded college education enrollment, increasing opportunities and incentives for rural students to pursue higher education (Wang et al., 2014). Given that the scale of college expansion varies by province and is related to the number of colleges within the province, this section controls for the college expansion effect by including the interaction term between province dummy variables and age group dummy variables, following Liang and Wang (2020). The results in Table 4, Column (1), show that the coefficient estimate for the interaction term is similar to the baseline regression. This suggests that even after accounting for college expansion, the NIP remains a significant factor in improving individual educational attainment.

Second, addressing the impact of school closure and merger. Chen and Li (2024) found that China's policy of school closure and merger has positively impacted rural students' educational attainment. If the implementation of this policy differs significantly between NIP pilot areas and other regions, it could lead to biased estimates. To address this concern, we follow Chen and Li (2024) and control for the extent to which students were affected by the school closure and merger. The results in Table 4, Column (2), show that our conclusions remain robust even after accounting for these factors.

Third, addressing the impact of free vocational high school (VHS) education. It is important to note that China initiated a policy in the autumn semester of 2012 to exempt all rural students from tuition fees at VHSs. If rural students in impoverished areas benefit disproportionately from this policy, neglecting its effects could lead to an overestimation of the NIP's influence on educational attainment. Given that VHS enrollment typically occurs within provincial boundaries, we construct an interaction term between poverty-stricken counties and provincial VHS enrollment rates and incorporate this into our model for estimation. Column 3 of Table 4 demonstrates that our results remain robust even after including this interaction term.

Fourth, addressing the impact of targeted university admissions. Since 2012, China has implemented a policy of directed recruitment for students from impoverished areas in university admissions. The oldest cohort affected by this policy would be those who were in grade three of senior high school (typically age 18) during the autumn semester of 2011. Ignoring this policy could confound the estimated effects of the NIP on educational outcomes. To account for this, we construct an interaction term between poverty-stricken counties and whether individuals belong to the affected age group, incorporating this into our model for estimation. Column 4 of Table 4 shows that our results remain robust even after including this interaction term.

Table 4
Estimated results after accounting for potential confounding policies.

	Explained variable: years of education			
	Excluding the impact of college expansion (1)	Excluding the impact of school closure and merger (2)	Excluding the impact of free vocational schools (3)	Exclude the impact of targeted enrollment (4)
NIP × Post	1.076*** (0.390)	1.002*** (0.381)	1.015*** (0.375)	0.883** (0.428)
Control Variables	Yes	Yes	Yes	Yes
Age group effects	Yes	Yes	Yes	Yes
County effects	Yes	Yes	Yes	Yes
Observations	2768	2768	2768	2768
R^2	0.309	0.304	0.305	0.304

Notes: 1. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively. 2. Robust standard errors clustered at the district level are shown in parentheses.

4.4. Mechanism analysis

Building on the theoretical analysis presented earlier, we posit that nutrition subsidies enhance students' educational attainment through two primary mechanisms: improved learning efficiency and increased parental educational aspirations. The impact on learning efficiency is believed to manifest in better health, cognitive abilities, and non-cognitive skills. This section leverages the baseline and follow-up data from the China Education Panel Survey (CEPS) to empirically investigate this mechanism. We employ a DID model based on students' grade levels and their schools' participation in the free lunch program. The baseline model is specified as follows:

$$M_{ist} = \beta_0 + \beta_1 treat_s \times grade_t + \omega X_{ist} + \gamma_t + \delta_s + \mu_{ist} \tag{3}$$

In the formula: M_{ist} is the outcome variable of interest in this study, which includes health level, cognitive ability, non-cognitive ability, and parental educational expectations. $treat_s$ is whether the school s provides free lunch. $grade_t$ is whether it is the eighth grade. X_{ist} is a vector of control variables, including student gender, age, ethnicity, father's education years, mother's education years, and family socioeconomic status. γ_t is the grade fixed effects. δ_s is the school fixed effects. μ_{ist} is the random error term.

The findings from equation (3), presented in Table 5, reveal a multifaceted benefit of nutrition funding. It not only improves students' health (by 0.33 standard deviations), but also enhances their cognitive (by 0.11 standard deviations) and non-cognitive abilities (by 0.26 standard deviations), suggesting a positive impact on learning efficiency. Additionally, nutrition funding fosters higher parental

Table 5
Results of the mechanism analysis.

	Health level (1)	Cognitive ability (2)	Non-cognitive ability (3)	Parental educational expectations (4)
treat × grade	0.326*** (0.064)	0.109*** (0.030)	0.262*** (0.077)	0.401** (0.185)
Control Variables	Yes	Yes	Yes	Yes
Grade effects	Yes	Yes	Yes	Yes
School effects	Yes	Yes	Yes	Yes
Observations	1942	1942	1942	1942
R^2	0.089	0.104	0.071	0.083

Notes: 1. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively. 2. Robust standard errors clustered at the district level are shown in parentheses.

educational expectations (by 0.4 years). In conclusion, these results strongly support Hypothesis H2, demonstrating that nutrition funding effectively promotes educational attainment by improving various student outcomes.

4.5. Heterogeneity analysis

This section examines the heterogeneous impact of the NIP across different parental education levels and regions (as shown in Table 6). The program significantly improves educational attainment for students with lower parental education levels and those in western regions. Although a positive effect is observed for students with higher parental education levels and in other regions, it is not statistically significant. This discrepancy may be attributed to the lower baseline levels of health, cognitive ability, and non-cognitive ability among students in western regions and those with less-educated parents. Since these groups have more room for improvement, the program's effects are more pronounced for them.

Given the positive correlation between parental education and child educational attainment, coupled with the educational lag in western regions, these findings suggest that the program plays a crucial role in narrowing educational disparities based on socioeconomic class and region. Ultimately, this promotes educational equity. This aligns with research on the importance of educational funding for disadvantaged students (Paxson and Schady, 2002).

5. Further analysis

5.1. Income effect and cost-benefit analysis

As discussed earlier, the central government in China has made significant investments in the NIP. This section evaluates its economic efficiency by examining its impact on income and conducting a cost-benefit analysis.

The empirical analysis from the previous section demonstrated that nutrition subsidies improve students' health and educational attainment. Health and education are critical components of human capital, which is essential for enhancing labor productivity (Mankiw et al., 1992). In a competitive labor market, individual wages are linked to labor productivity. Thus, the NIP can foster income growth by strengthening individuals' health and educational human capital. Table 7 presents the estimated results of the NIP's impact on the income of beneficiary children. Columns (1) and (2) use the logarithm and level of income as the dependent variables, respectively. The findings indicate that each additional year of program exposure results in a 10.3% increase in income, translating to an average annual increase of 3191 yuan.

Table 6
Results of the heterogeneity analysis.

	Dependent variable: years of education			
	Low parental education (1)	High parental education (2)	Western region (3)	Non-western region (4)
NIP × Post	1.037***	0.227	1.623**	0.591
	(0.399)	(1.098)	(0.667)	(0.488)
Control Variables	Yes	Yes	Yes	Yes
Age group effects	Yes	Yes	Yes	Yes
County effects	Yes	Yes	Yes	Yes
Observations	2386	292	920	1848
R^2	0.299	0.408	0.274	0.325

Notes: 1. ***, **, and * denote significance levels of 1 %, 5 %, and 10 %, respectively. 2. Robust standard errors clustered at the district level are shown in parentheses. 3. Low parental education level refers to an average parental education of 9 years or less, while high parental education level refers to an average parental education of more than 9 years.

Table 7
Estimated Results of the Income Effect of the NIP.

	Income (log) (1)	Income (level) (2)
NIP × Years of Benefit	0.103**	3190.891**
	(0.048)	(1442.234)
Control Variables	Yes	Yes
Age group effects	Yes	Yes
County effects	Yes	Yes
Observations	1527	1527
R^2	0.238	0.238

Notes: 1. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively. 2. Robust standard errors clustered at the district level are shown in parentheses.

We assess the benefits and costs of the NIP using back-of-the-envelope analysis. From the perspective of benefits, each year of nutrition subsidy can increase an individual's annual income by 3191 yuan. Adjusting this amount to the 2011 price level yields 2,600 yuan per year. Over a 30-year working life, this translates to a total income increase of 78,000 yuan per individual.

On the cost side, there are three main factors: First, direct food subsidies from the central government: For the sample analyzed, the subsidy period for beneficiary students was from 2011 to 2014, with a subsidy standard of 600 yuan per person per year. Second, implicit rent for new canteens built for the NIP: This includes the costs related to land, construction, and equipment. Third, operational costs of the canteens: This encompasses staff salaries, utilities, and fuel expenses. Given the challenge of accurately calculating the average per capita share of canteen rent and operating costs, and considering that food costs typically represent 10%-30% of the total cost, this paper estimates the annual average per capita cost of nutrition subsidies to be between 2,000 and 6,000 yuan.

In conclusion, the economic benefits that the NIP brings to beneficiary children significantly surpass the investment costs. However, this analysis may underestimate the program's full benefits. First, educational improvements often generate externalities (Chen et al., 2020). The NIP may not only increase the income of beneficiaries through enhanced education but also potentially benefit other groups via these externalities. Second, the benefits of nutrition subsidies extend beyond income growth to include enhancements in health, cognitive abilities, and non-cognitive skills, which are not fully captured in this calculation.

5.2. Impact of the local pilot programs

Some regions have implemented local pilot programs for the NIP (LNIP). Table 8 presents the results of these local programs' impact on students' educational attainment. Notably, the findings reveal no significant impact on students' likelihood of entering high school or college, nor on the number of years of education they receive.

Table 8
Effects of the LNIP.

	High school or above (1)	College or above (2)	Education years (3)
LNIP × Post	−0.010	0.027	0.113
	(0.044)	(0.043)	(0.296)
Control Variables	Yes	Yes	Yes
Age group effects	Yes	Yes	Yes
County effects	Yes	Yes	Yes
Observations	3028	3028	3028
R2	0.261	0.236	0.308

Notes: 1. ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively. 2. Robust standard errors clustered at the district level are shown in parentheses.

This paper argues that three main reasons limit the effectiveness of local pilot programs. First, funding for nutrition subsidies in these areas relies heavily on local government self-financing, constrained by local fiscal conditions and administrative priorities. This makes it challenging to ensure long-term stability and effective quality control of subsidies.

Additionally, local pilot programs are subject to less rigorous supervision compared to national-level programs, leading to potential negligence and inconsistencies in policy implementation. For example, among the 699 national pilot counties, 678 began providing nutritional meals in the first year of the project. In contrast, only 288 out of 616 local pilot counties initiated nutritional meal provision in the same period.

Finally, national pilot programs are often implemented in economically disadvantaged, poverty-stricken areas, where rural students are more likely to suffer from malnutrition. As a result, the policy effects of the NIP are more pronounced in these regions. Conversely, local pilot counties cover some economically developed regions, such as Shanghai, Jiangsu, and Zhejiang, where rural students typically have better nutritional status, thereby limiting the effectiveness of the NIP.

6. Conclusion and policy implications

This paper investigates the long-term impact of the Nutrition Improvement Program (NIP) on educational attainment in rural China. Utilizing a Cohort DID quasi-natural experiment approach and data from the 2019 China Household Finance Survey (CHFS), the study reveals the NIP's significant effectiveness. Beneficiaries saw substantial gains, with a 12.9% increase in the probability of entering high school and a 13.3 % increase in the probability of attending college. These positive impacts were consistently observed across various robustness checks.

The NIP enhances educational attainment in rural China through several mechanisms: addressing nutritional deficiencies, improving cognitive abilities, developing non-cognitive skills, and increasing parental educational expectations. Notably, the program has a more substantial impact on students from disadvantaged backgrounds (lower parental education) and in western regions of China. This underscores the NIP's role in narrowing educational disparities and promoting equity across different social classes and geographic regions, ultimately contributing to a more equitable society.

Furthermore, the NIP demonstrates a remarkable return on investment, with economic benefits significantly outweighing the program's costs. This underscores its financial viability and potential to contribute to long-term economic growth and development. However, the lack of significant impact on educational attainment from locally funded NIP programs is notable. This is likely due to their reliance on local fiscal conditions and inadequate supervision, underscoring the need for centralized support and robust oversight mechanisms.

In light of these compelling findings, the paper proposes the following policy recommendations to further amplify the NIP's transformative impact.

First, expand centralized nutrition subsidies. To address the persistent nutrition and health gap between rural and urban students, the government should substantially increase the funding and coverage of the centrally funded NIP. This expansion will ensure that more students receive the essential nutrition support they need to excel academically. By investing in this long-term initiative, the government can play a crucial role in reducing rural poverty and bridging the urban-rural divide.

Second, increase funding intensity for vulnerable groups. Given the disproportionate impact of nutrition and health challenges on students from impoverished families, the government should implement differentiated subsidy standards tailored to regional economic conditions and family economic status. Integrating these targeted measures with existing poverty alleviation policies can maximize the program's benefits and ensure comprehensive support. Additionally, recognizing the substantial economic returns from early childhood nutrition investments (Heckman and Corbin, 2016), pilot policies to extend funding periods—such as increasing preschool education funding in economically underdeveloped regions—could generate significant long-term economic gains.

Third, strengthen supervision of local programs. To address inconsistencies in the implementation of NIP due to local funding constraints and potential lax supervision, the central government should establish robust incentive mechanisms for local governments. Simultaneously, it should enhance guidance and oversight of local NIP projects. This approach will ensure effective implementation, improve the overall quality and impact of subsidies, and maximize the program's influence on educational attainment.

By adopting these comprehensive policy recommendations, the government can further amplify the NIP's positive impact, fostering a generation of well-educated, healthy, and productive citizens who contribute to China's continued progress and prosperity. The NIP exemplifies the transformative potential of targeted interventions in addressing educational disparities and promoting social equity, paving the way for a brighter future for all Chinese children.

The contributions of this paper are twofold. On the one hand, we evidence the significant positive long-term impact of the NIP on the beneficiary children. The findings show that each additional year of program exposure results in a substantial increase in income. This demonstrates the economic value of investing in nutrition programs for children, particularly in terms of enhancing their future earning potential. Beyond the direct economic benefits, the analysis highlights the broader implications of the NIP for human capital development. The program contributes to improvements in long-term effects, including health and education, which are critical components of human capital. These improvements can lead to higher labor productivity and better employment opportunities, thereby reducing poverty and inequality.

On the other hand, the findings in this paper provide actionable policy recommendations. Policymakers are encouraged to consider expanding the NIP and similar nutrition programs, given their demonstrated effectiveness in improving children's outcomes. Additionally, the analysis suggests the importance of long-term investment in nutrition and education to support sustainable economic development.

CRediT authorship contribution statement

Zhen Guan: Data curation, Formal analysis, Writing – original draft. **Yang He:** Methodology, Writing – review & editing, Validation. **Xinjie Shi:** Data curation, Methodology. **Chen Zhang:** Funding acquisition, Conceptualization, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

Afridi, F., 2010. Child welfare programs and child nutrition: evidence from a mandated school meal program in India. J. Dev. Econ. 92 (2), 152–165. https://doi.org/10.1016/j.jdeveco.2009.02.002.

Becker, G., 1962. Investment in human capital: a theoretical analysis. J. Polit. Econ. 70, 9–49. https://doi.org/10.1086/258724.
Behrman, J.R., Rosenzweig, M.R., 2004. Returns to birthweight. Rev. Econ. Stat. 86 (2), 586–601. https://doi.org/10.1162/003465304323031139.
Belot, M., James, J., 2011. Healthy school meals and educational outcomes. J. Health Econ. 30 (3), 489–504. https://doi.org/10.1016/j.jhealeco.2011.02.003.
Buttenheim, A., Alderman, H., Friedman, J., 2011. Impact evaluation of school feeding programs in Lao PDR. J. Dev. Effect. 3 (4), 520–542. https://doi.org/10.1080/19439342.2011.634511.
Chakraborty, T., Jayaraman, R., 2019. School feeding and learning achievement: evidence from India's midday meal program. J. Dev. Econ. 139, 249–265. https://doi.org/10.1016/j.jdeveco.2018.10.011.
Chen, A., Li, Y., 2024. Long-term effects of early-life education intervention on children's outcomes: evidence from school consolidation in rural China. J. Asian Econ. 93, 1–17. https://doi.org/10.1016/j.asieco.2024.101751.
Chen, Y., Fan, Z., Gu, X., Zhou, L., 2020. Arrival of young talent: the send-down movement and rural education in China. Am. Econ. Rev. 110 (11), 3393–3430. https://doi.org/10.1257/aer.20191414.
Currie, J., 2009. Healthy, wealthy and wise: socioeconomic status, poor health in childhood and human capital development. J. Econ. Lit. 47 (1), 87–122. https://doi.org/10.1257/jel.47.1.87.
Duan, X., Yinhe, L., Peng, X., 2024. Free school meals and cognitive ability: evidence from China's student nutrition improvement plan. Health Econ. 33 (7), 1480–1502. https://doi:10.1002/hec.4824.
Duflo, E., 2001. Schooling and labor market consequences of school construction in Indonesia: evidence from an unusual policy experiment. Am. Econ. Rev. 91 (4), 795–813. https://doi.org/10.1257/aer.91.4.795.
Fang, G., Zhu, Y., 2022. Long-term impacts of school nutrition: evidence from China's school meal reform. World Dev. 153, 1–14. https://doi.org/10.1016/j.worlddev.2022.105854.
Fang, S., Huang, J., Curley, J., Birkenmaier, J., 2018. Family assets, parental expectations, and children educational performance: an empirical examination from China. Child Youth Serv. Rev. 87, 60–68. https://doi.org/10.1016/j.childyouth.2018.02.018.
Frisvold, D.E., 2015. Nutrition and cognitive achievement: an evaluation of the school breakfast program. J. Public Econ. 124, 91–104. https://doi.org/10.1016/j.jpubeco.2014.12.003.
Gelli, A., Aurino, E., Folson, G., 2019. A school meals program implemented at scale in Ghana increases height-for-age during midchildhood in girls and in children from poor households: a cluster randomized trial. J. Nutr. 149 (8), 1434–1442. https://doi.org/10.1093/jn/nxz079.
Gertler, P., 2004. Do conditional cash transfers improve child health? evidence from Progresa's control randomized experiment. Am. Econ. Rev. 94 (2), 336–341. https://doi.org/10.1257/0002828041302109.
Gong, J., Lu, Y., Song, H., 2018. The effect of teacher gender on students' academic and noncognitive outcomes. J. Labor Econ. 36 (3), 743–778. https://doi.org/10.1086/696203.
Gundersen, C., Kreider, B., Pepper, J., 2012. The impact of the national school lunch program on child health: a nonparametric bounds analysis. J. Econom. 166 (1), 79–91. https://doi.org/10.1016/j.jeconom.2011.06.007.
Heckman, J.J., Corbin, C.O., 2016. Capabilities and skills. J. Human Dev. Capabil. 17 (3), 342–359. https://doi.org/10.1080/19452829.2016.1200541.
Hinrichs, P., 2010. The effects of the national school lunch program on education and health. J. Policy Anal. Manage. 29 (3), 479–505. https://doi.org/10.1002/pam.20506.
Imberman, S.A., Kugler, A.D., 2014. The effect of providing breakfast in class on student performance: the effect of providing breakfast in class. J. Policy Anal. Manage. 33 (3), 669–699. https://doi.org/10.1002/pam.21759.
Li, H., Loyalka, P., Rozelle, S., Wu, B., 2017. Human capital and China's future growth. J. Econ. Perspect. 31 (1), 25–48. https://doi.org/10.1257/jep.31.1.25.
Li, P., Lu, Y., Wang, J., 2016. Does flattening government improve economic performance? evidence from China. J. Dev. Econ. 123 (1), 18–37. https://doi.org/10.1016/j.jdeveco.2016.07.002.
Liang, X., Hu, Q., Hou, X., Xu, J., 2024. The national nutrition improvement program and the equity of educational opportunities: evidence from rural China. Appl. Econ. 3, 1–17. https://doi.org/10.1080/00036846.2024.2323548.
Lucas, R.E., 1988. On the mechanics of economic development. J. Monet. Econ. 22 (1), 3–42. https://doi.org/10.1016/0304-3932(88)90168-7.
Lundborg, P., Rooth, D.O., Alex-Petersen, J., 2022. Long-term effects of childhood nutrition: evidence from a school lunch reform. Rev. Econ. Stud. 89 (2), 876–908. https://doi.org/10.1093/restud/rdab028.
Luo, H., Hu, Q., 2024. A re-examination of the influence of human capital on urban-rural income gap in China: college enrollment expansion, digital economy and spatial spillover. Econ. Anal. Policy. 81, 494–519. https://doi.org/10.1016/j.eap.2023.12.018.
Mankiw, N.G., Romer, D., Weil, D.N., 1992. A contribution to the empirics of economic growth. Q. J. Econ. 107 (2), 407–437. https://doi.org/10.2307/2118477.
McEwan, P.J., 2013. The impact of Chile's school feeding program on education outcomes. Econ. Educ. Rev. 32, 122–139. https://doi.org/10.1016/j.econedurev.2012.08.006.
Paxson, C., Schady, N.R., 2002. The allocation and impact of social funds: spending on school infrastructure in Peru. World Bank Econ. Rev. 16 (2), 297–319. https://doi.org/10.1093/wber/16.2.297.
Popkin, B.M., 2008. Will China's nutrition overwhelm its health care system and sloe economic growth. Health Aff. 27 (4), 1064–1076. https://doi.org/10.1377/hlthaff.27.4.1064.
Schanzenbach, D.W., 2009. Do school lunches contribute to childhood obesity. J. Hum. Resour. 44 (3), 684–709. https://doi.org/10.1353/jhr.2009.0021.
Wang, G., Shi, X., Golley, J., 2024. Feed the children, free the women? evidence from the China rural nutrition improvement program. China Econ. Rev. 87 (6), 1–16. https://doi.org/10.1016/j.chieco.2024.102228.
Wang, H., Cheng, Z., 2022. Kids eat free: school feeding and family spending on education. J. Econ. Behav. Organ. 193, 196–212. https://doi.org/10.1016/j.jebo.2021.11.023.
Wang, X., Fleisher, B.M., Li, H., Li, S., 2014. Access to college and heterogeneous returns to education in China. Econ. Educ. Rev. 42, 78–92. https://doi.org/10.1016/j.econedurev.2014.05.006.
Yamamoto, Y., Holloway, S.D., 2010. Parental expectations and children's academic performance in sociocultural context. Educ. Psychol. Rev. 22 (3), 189–214. https://doi.org/10.1007/s10648-010-9121-z.
Zheng, X., Ren, J., Chen, D., Fang, X., 2023. School feeding and children's noncognitive skills: evidence from the nutrition improvement program in rural China. Appl. Econ. 55 (55), 6459–6478. https://doi.org/10.1080/00036846.2022.2156472.
Zhou, Y., Ren, J., Zheng, X., 2024. Feeding for a brighter future: the long-term labor market consequences of school meals in rural China. Econ. Hum. Biol. 52, 1–13. https://doi.org/10.1016/j.ehb.2023.101335.