Food Policy 144 (2026) 103190

Contents lists available at ScienceDirect

Food Policy

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

Opportunity beyond the first 1000 days: school feeding and child health in rural China

Zhen Liu [a,b,c,*], Zuhui Huang [a]

[a] China Academy for Rural Development (CARD) and School of Public Affairs, Zhejiang University, 310058 Hangzhou, China
[b] College of Economics and Management, Nanjing Agricultural University, 210095 Nanjing, China
[c] Center for Development Research (ZEF), University of Bonn, 53113 Bonn, Germany

ARTICLE INFO

JEL classification:
Q18
I15
O15

Keywords:
School feeding
Stunting
Health inequality
Child nutrition

ABSTRACT

Health inequalities often originate in early childhood, but millions of children miss the critical intervention window of the first 1000 days of life. We investigate whether nutritional investments during the school years can help these children recover. To do so, we analyze China's Nutrition Improvement Program (NIP), the world's third-largest school feeding program. Using nationally representative longitudinal data from 2010 to 2018 and difference-in-differences models, we find substantial and cumulative gains in height-for-age and reductions in stunting. The program also lowers overweight and obesity, suggesting that school feeding can alleviate undernutrition without exacerbating overnutrition. Moreover, children with poorer nutritional status and lower socioeconomic status experience greater improvements from the NIP; among them, those with better access to healthcare services in early life are more likely to recover from stunting. Shifts in dietary patterns and reduced morbidity likely drive the program's effects. Our findings indicate that interventions targeting school-age children can generate meaningful growth recovery and reduce health disparities that emerge early in life.

1. Introduction

Health and economic disparities often originate in early childhood (Case et al., 2002). Nutritional deficits during the first 1000 days of life can profoundly impact physical development, human capital formation, and economic well-being (Attanasio, 2026). Global progress in reducing child undernutrition has slowed in recent years, with more than one in five children under five still stunted (UNICEF et al., 2025). An important question is whether children who fall behind early in life can recover later. Emerging research suggests that the school-age years may offer a second window for growth recovery (Adhvaryu et al., 2023; Georgiadis and Penny, 2017; Hirvonen, 2013; Prentice et al., 2013), but empirical evidence from large-scale nutrition interventions is scarce.

School feeding programs (SFPs) provide a particularly relevant setting in which to examine this question. Reaching about 466 million children daily, SFPs are the world's largest child health intervention (Alderman et al., 2024). This paper focuses on China's Nutrition Improvement Program (NIP), the world's third-largest SFP. Introduced in late 2011, the NIP provides free, government-subsidized lunches to rural primary and secondary school students. By 2020, it reached nearly 40 million children, roughly a quarter of China's population in this age group (Ministry of Education of China, 2021). Its phased rollout creates quasi-experimental variation in program exposure across regions and birth cohorts. We exploit this variation within a nationally representative longitudinal dataset to evaluate the program's impact on child health.

While existing research documents the average nutritional benefits of SFPs, less is known about whether these gains reduce health disparities. Some studies find greater improvements among children with poorer baseline nutritional status (Adhvaryu et al., 2023; Gelli et al., 2019). Others report larger gains among better-nourished children (Singh et al., 2014; Wang et al., 2023). Whether school feeding narrows or widens these disparities depends on how children's existing health conditions shape the returns to additional nutritional inputs. This is a key question we develop in the conceptual framework.

A growing body of research has examined the effects of the NIP on cognitive skills, educational attainment, labor market outcomes, and household expenditure (Duan et al., 2024; Fang and Zhu, 2022; Guan et al., 2025; Liang et al., 2025; Wang et al., 2024; Wang and Cheng, 2022; Zhao et al., 2024; Zheng et al., 2023; Zhou et al., 2024), but less attention has been paid to nutrition and health outcomes. While recent studies suggest that the program reduces anemia and stunting and

* Corresponding author at: China Academy for Rural Development (CARD) and School of Public Affairs, Zhejiang University, 310058 Hangzhou, China.
E-mail addresses: zhenliu0510@gmail.com (Z. Liu), zhhuang@zju.edu.cn (Z. Huang).

https://doi.org/10.1016/j.foodpol.2026.103190
Received 26 February 2026; Received in revised form 3 September 2026; Accepted 4 September 2026
0306-9192/

increases child height (Ren et al., 2023; Wang et al., 2020; Wang et al., 2019; Wang et al., 2026), evidence on whether it influences health disparities remains limited and inconclusive. Specifically, at least two studies report larger anthropometric improvements among children with relatively better nutritional status (Wang et al., 2023; Zhou et al., 2021).

Three additional gaps motivate our study. First, despite growing concerns about overweight and obesity in low- and middle-income countries (LMICs) (Alderman et al., 2024), existing research focuses on undernutrition outcomes. SFPs designed to address nutritional deficits may also provide excess calories, resulting in potential trade-offs that must be considered when assessing their overall nutritional impact. Second, while many studies examine the dietary impacts of SFPs, less is known about their effects on child morbidity, a plausible but understudied pathway through which improved nutrition may contribute to physical growth.

Third, how school feeding interacts with other health interventions is poorly understood. Children often do not enter these programs with a clean slate. In China, for example, many rural children were already exposed to the New Cooperative Medical Scheme (NCMS), a nationwide health insurance reform introduced roughly a decade before the NIP that expanded access to maternal and child healthcare services. Prior health investments may shape children's capacity to benefit from later nutritional interventions (Abramovsky et al., 2025; Alderman et al., 2014; Attanasio, 2026).

Our study addresses these gaps. Using nationally representative longitudinal data from the China Family Panel Studies (CFPS) between 2010 and 2018, we first examine the NIP's causal effects on anthropometric outcomes. Then, we ask whether these effects are more pronounced for children with poorer initial nutritional status and from disadvantaged households. Next, we examine whether exposure to the NCMS in early life shapes these outcomes. To understand how the program affects child health, we also analyze its effects on dietary intake and morbidity as potential pathways.

We find that exposure to the NIP increases height and reduces stunting. These benefits accumulate with continued exposure and are concentrated among children with poorer initial nutritional status and disadvantaged socioeconomic backgrounds. The NIP also reduces overweight and obesity, suggesting that school feeding need not involve a trade-off between reducing undernutrition and preventing overnutrition. Children exposed to the NCMS in early life are more likely to recover from stunting after being exposed to the NIP. Improvements in diets and reductions in morbidity appear to contribute to these nutritional improvements.

Our study contributes to the literature in three ways. First, we provide evidence that school feeding can stimulate growth recovery and reduce health inequalities. Second, we demonstrate that the benefits of nutritional interventions depend on prior health investments, underscoring the importance of policy coordination across stages of child development. Third, we identify reduced morbidity as a potential pathway through which school feeding improves health, complementing earlier work that links SFPs to educational attainment and adult labor market outcomes (Guan et al., 2025). Fewer illness episodes can increase attendance and time on task, thereby translating nutritional inputs into human capital.

The remainder of the paper is organized as follows. Section 2 presents the conceptual framework. Section 3 provides institutional background. Section 4 describes the data and variables, and Section 5 outlines the empirical strategy. Section 6 presents the results. Section 7 discusses the implications and limitations of the findings, and concludes.

2. Conceptual framework

SFPs can improve child health through two related channels. First, nutrient-dense school meals increase the intake of energy, protein, and essential micronutrients that many children in LMICs, including rural China during our study period, do not consume in sufficient quantities. Improved nutrition supports skeletal and muscle development, allowing nutritional investments to accumulate into measurable gains in height over time (Millward, 1995). Second, improved nutrition may reduce morbidity. Infections and inflammation divert metabolic resources away from physical growth and increase nutritional requirements (Prentice et al., 2013). By improving dietary quality and micronutrient intake, school feeding may strengthen immune function, reducing the frequency and severity of illness and allowing more metabolic resources to support physical growth.

Although school feeding is expected to improve child health on average, the magnitude depends on which constraints are binding. Multiple factors influence physical growth, including inadequate dietary intake, infections, caregiving environments, early-life conditions, and so on (Prendergast and Humphrey, 2014). If inadequate nutrition is the primary constraint, school feeding can address this issue by increasing nutrient availability. Under these circumstances, children with poorer nutritional status may benefit more. By contrast, children in better health may already receive adequate nutrition at home, so school meals may largely substitute for existing food consumption rather than increase total nutrient intake.

Alternatively, poor nutritional status does not necessarily mean that inadequate food intake is the sole constraint on growth. Undernourished children may also suffer from enteric dysfunction, chronic infection, or persistent inflammation, which can impair nutrient absorption and increase nutritional requirements (Bourke et al., 2019). For these children, school meals alone may be insufficient to overcome the underlying constraints on growth. As a result, children who enter school in relatively better health may benefit more.

Hence, the health effects of school feeding are context-dependent. Examining the heterogeneous treatment effects of the NIP helps to assess its potential to reduce health inequalities in China.

Early-life health investments may also influence children's responses to later nutritional interventions. In the Chinese context, the NCMS is a key early-life investment. It expanded access to maternal and child healthcare before the introduction of the NIP. By improving access to preventive and basic healthcare, the NCMS may have prevented or mitigated conditions that impair nutrient absorption and physical development. Consequently, children exposed to the NCMS early in life may have entered school with a greater capacity to convert the nutritional inputs provided by the NIP into physical growth.

Our empirical analysis addresses three questions: (a) whether NIP exposure improves child health on average, (b) whether disadvantaged children experience greater improvements, and (c) whether early-life exposure to healthcare services shapes the benefits of the NIP.

3. Institutional background

3.1. School feeding intervention: the Nutrition Improvement Program (NIP)

Although child nutritional status in China has improved over time, rural children continue to face higher risks of undernutrition and poorer physical growth than their urban counterparts. During the 1990s and 2000s, the urban–rural height gap widened considerably before beginning to narrow in the 2010s (Supplementary Fig. A1). Against this background, China launched the NIP in late 2011, with large-scale implementation beginning in 2012.

The NIP provides free lunches on each school day to students in Grades 1–9 in rural primary and junior secondary schools. Meals are prepared and served on-site, mainly through school canteens, and are designed as full midday meals rather than supplementary snacks.

The program follows a county-based pilot structure. Participating counties are classified as either national pilot counties or local pilot counties based on funding sources. National pilot counties receive full financing from the central government, while local pilot counties are financed by provincial governments with central matching subsidies that depend on local fiscal capacity. Notably, pilot status is assigned by higher-level governments rather than determined through county applications.

Between 2012 and 2020, the NIP expanded rapidly. The number of national pilot counties increased from 657 to 727, and the number of local pilot counties increased from 288 to 1005 (Fig. 1). By 2020, about 60% of Chinese counties had adopted the program, serving around 40 million students. Supplementary Fig. A2 shows the locations of the pilot counties. In 2012, the national pilot counties were among the most economically disadvantaged areas in China, with per capita GDP and rural household incomes far below the national average (Supplementary Table A1). Local pilot counties had somewhat better economic conditions than national pilot counties but also lagged behind the national level. Therefore, unlike the near-universal SFPs in countries such as Brazil and India, the NIP is explicitly targeted toward poorer regions where undernutrition risks are higher.[1]

The NIP's meal subsidy increased over time, rising from Chinese Yuan (CNY) 3 per student per school day at the program's inception to CNY 4 in late 2014 and CNY 5 in 2021.[2] The 2014 adjustment increased the purchasing power of the subsidy. As shown in Supplementary Fig. A3, the original subsidy was often insufficient to finance a nutritionally balanced lunch in some provinces. However, the higher subsidy of CNY 4 can finance such a lunch in all provinces. Meal subsidies can only be used to purchase food and condiments. Non-food expenditures, including canteen construction, kitchen equipment, and staff salaries, are funded separately.

Three institutional features imply that most eligible rural children are exposed to the NIP. First, compulsory education is nearly universal in China, with primary school enrollment rates exceeding 99%.[3] Among students in the relevant grades, the eligible and enrolled populations are nearly identical. Second, the NIP covers all rural primary and junior secondary schools in participating counties, even including private schools that are rare in rural areas. Third, once a county enters the program, it does not exit. Thus, eligible children in participating counties remain exposed to the NIP until they graduate from junior secondary school, migrate to an urban area, or move to a county outside the program.

3.2. *Early-life intervention: the New Cooperative Medical Scheme (NCMS)*

The NIP entered a policy environment already shaped by earlier health reforms, particularly the New Cooperative Medical Scheme (NCMS). Launched in 2002, the NCMS expanded health insurance coverage among rural residents, who had previously relied on out-of-pocket healthcare spending. The NCMS was implemented gradually across counties and financed through household contributions and government subsidies (Hsiao et al., 2014). In the early years, each enrollee paid CNY 10 annually, matched by at least CNY 10 from the government. Although contribution levels increased over time, substantial government support remains. By 2011, the NCMS covered over 97% of the rural population, reimbursing inpatient and, in many areas, outpatient services.

The NCMS also expanded access to maternal and child healthcare services, including prenatal and postnatal checkups, folic acid supplementation during pregnancy, and reimbursement for hospital delivery costs (National Health Commission of China, 2018). Between 2003 and 2011, the hospital delivery rate increased from 74% to nearly universal coverage, and maternal and child mortality declined substantially (Supplementary Figs. A4 and A5). Some studies document positive effects of the NCMS on healthcare utilization and child health outcomes (Babiarz et al., 2010; Huang and Liu, 2023). These improvements may have increased children's capacity to benefit from later nutritional interventions.

4. Data and measures

4.1. *Data and sample*

We use data from the CFPS, a nationally representative longitudinal survey conducted since 2010. The CFPS covers more than 600 communities (i.e., urban neighborhoods and rural villages) in 25 provinces and collects information at the individual-, household-, and community-level information through a three-stage stratified random sampling design. All household members are interviewed about a wide range of topics, including health, education, and socioeconomic conditions. Most of the questions refer to information from the previous year.

We use the first six survey waves (2010, 2011, 2012, 2014, 2016, and 2018). The 2020 and 2022 waves are excluded because the COVID-19 pandemic disrupted schooling, food supply chains, and healthcare access, potentially confounding the effects of the NIP.

The analysis focuses on children born between 1996 and 2012. Children born before 1996 had already completed junior secondary school before the NIP was introduced, whereas those born after 2012 had not yet reached primary school age (six years old) by 2018. The sample is further limited to children enrolled in junior secondary school or below and living in rural areas at the time of the interview. Children younger than two are excluded because infant health indicators differ from those used for older children. Supplementary Table A2 summarizes the sample construction process. The final sample contains 13,099 observations from 4961 children. Table 1 reports descriptive statistics for all variables.

4.2. *NIP exposure*

Our primary treatment variable is a binary indicator equal to one if a child is exposed to the NIP in a given year. We collect county-level implementation dates from official policy documents, government announcements, or education bureau reports. Among the 149 rural counties in the CFPS sample, 30 are national pilot counties and 23 are local pilot counties by 2018.

A child is considered first exposed in the later of two years: (i) the year the county adopted the program or (ii) the first year the child entered an eligible grade.[4] The treatment indicator is absorbing. Once a child is observed as treated, the child remains treated in all subsequent waves because county participation is permanent and children leave the sample after completing junior secondary school. Supplementary Table A3 reports the distribution of treated and untreated observations across survey waves and pilot types. National pilot counties contribute the majority of treated observations in every wave.

We also construct two continuous treatment variables. The first is exposure duration, defined as the number of years the child has been exposed to the NIP by the time of each survey wave. The second is cumulative subsidy intensity, measured as the cumulative value of per-student daily subsidies received over all years of exposure (in CNY, 2011 prices).

[1] The designs of school feeding programs across countries can be found at https://globalallianceagainsthungerandpoverty.org/policy-instruments/school-meals-programmes/.

[2] The average CNY/USD exchange rate was 6.5 in 2010–2018. Thus, CNY 3, 4, and 5 are roughly equivalent to USD 0.46, 0.62, and 0.77.

[3] Available online: https://hudong.moe.gov.cn/jyb_sjzl/sjzl_fztjgb/201907/t20190724_392041.html.

[4] Consider a county that implemented the NIP in 2013. A child who entered Grade 1 in 2012 would be classified as first exposed in 2013, when the program became available locally. A child who entered Grade 1 in 2015 would be classified as first exposed in 2015.

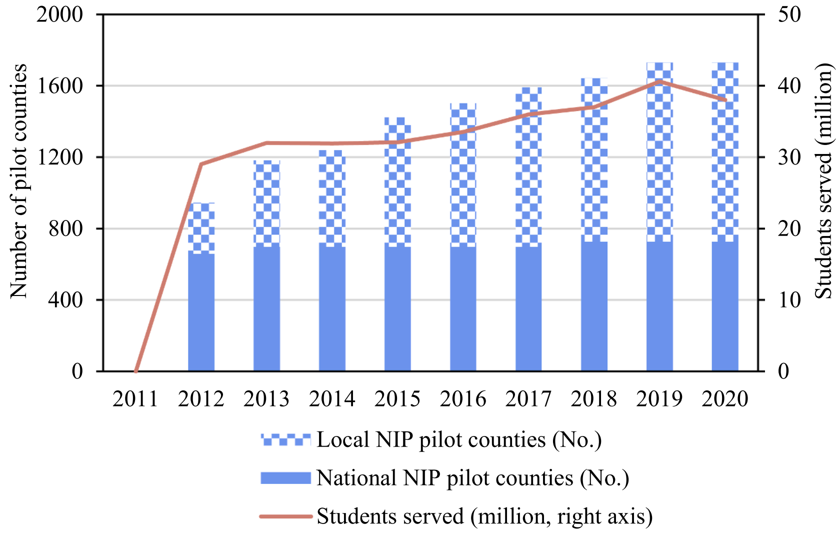

Fig. 1. Rollout of the Nutrition Improvement Program (NIP) in China, 2011–2020. *Source*: Authors' tabulations from the NIP administrative data (Ministry of Education of China, various years).

Table 1
Summary statistics.

	NIP treatment group		NIP control group	
	Mean	SD	Mean	SD
School feeding				
NIP = 1 (currently treated)	0.446	0.497	0.000	0.000
Early-life intervention exposure				
NCMS = 1 (fully exposed at ages 0–2)	0.292	0.455	0.352	0.478
Health outcomes				
HAZ (Height-for-age z-score)	−1.068	1.661	−0.690	1.552
Stunted = 1	0.279	0.448	0.190	0.392
Thinness	0.134	0.340	0.133	0.340
BAZ (BMI-for-age z-score)	−0.010	1.736	−0.153	1.692
Overweight = 1	0.271	0.445	0.235	0.424
Obesity = 1	0.130	0.337	0.105	0.306
Dietary intake				
Meat (past week) = 1	0.783	0.413	0.825	0.380
Milk (past week) = 1	0.349	0.477	0.423	0.494
Nuts (past week) = 1	0.401	0.490	0.469	0.499
Eggs (past week) = 1	0.640	0.480	0.740	0.439
Pickled foods (past week) = 1	0.301	0.459	0.346	0.476
Fried and puffed foods (past week) = 1	0.358	0.480	0.363	0.481
Morbidity				
Illness-related school absence (past month) = 1	0.045	0.208	0.042	0.200
Illness frequency (past month)	0.382	0.861	0.409	0.881
Outpatient visits (past month)	0.271	0.722	0.314	0.762
Outpatient visits (past year)	1.542	2.915	1.843	3.285
Hospitalization (past year) = 1	0.076	0.264	0.055	0.228
Morbidity Index	−0.028	1.040	−0.008	1.011
Demographics				
Age	9.550	3.663	9.200	3.901
Male = 1	0.532	0.499	0.523	0.500
Ethnic minority = 1	0.288	0.453	0.042	0.200
Family background				
Average parental education (years)	6.318	3.377	7.774	2.950
Family size	5.274	1.728	5.248	1.833
ln(per capita income, 2010 prices)	8.511	0.951	8.804	0.905
2010 village characteristics				
Nearby healthcare facility (hospitals and clinics) = 1	0.800	0.400	0.856	0.351
Nearby pharmacy = 1	0.358	0.479	0.344	0.475
Piped drinking water supply = 1	0.266	0.442	0.370	0.483
Observations	5100		7999	

Notes: Authors' tabulations of 2010–2018 CFPS data. Dietary intake information is only available from 2010 to 2014.

4.3. Early-life exposure to the NCMS

To capture early-life exposure to healthcare services, we construct a binary indicator for whether a child was fully exposed to the NCMS during the first two years of life. For each child, we compare the year in which the child's village first implemented the NCMS with the child's birth year. A child is classified as fully exposed if the NCMS had been available in their village at least one year before birth, covering the first 1000 days from the prenatal period through the child's second birthday. This indicator is time-invariant at the individual level. Roughly 30% of observations are classified as fully exposed to the NCMS in early life, with similar shares in the NIP treatment and control groups (Table 1).

4.4. Child nutritional outcomes

We use anthropometric outcomes to measure child nutritional status. We focus on height-for-age z-scores (HAZ) and stunting as measures of undernutrition and additionally examine thinness. HAZ is a continuous measure of linear growth, with lower values indicating chronic undernutrition. Stunting is a binary indicator equal to one if HAZ < -2. Thinness is a binary indicator equal to one if BMI-for-age z-score (BAZ) < -2 and captures acute undernutrition among children older than five years.

We also examine BMI-for-age z-scores (BAZ), overweight, and obesity as indicators of overnutrition. Overweight and obesity are binary variables, defined as BAZ > 1 and >2, respectively.

All z-scores are calculated using age- and sex-specific WHO growth references. For children aged 2 to under 5 years, we use the WHO Child Growth Standards (WHO, 2006), while for children older than five years we use the 2007 WHO Growth Reference (de Onis et al., 2007). We drop observations with biologically implausible values (HAZ below -6 or above 6, BAZ below -5 or above 5).

4.5. Mechanism variables

4.5.1. Dietary intake

Dietary information is available only in the 2010, 2011, 2012, and 2014 waves. The survey records binary indicators for whether a child consumed specific food categories during the previous week. We focus on two groups of foods. The first consists of protein-rich foods, including meat, milk, eggs, and nuts. The second includes foods associated with poorer dietary quality, namely pickled foods, which are high in salt and nitrates, and fried and puffed foods, which are high in fat. We exclude fruit and vegetable consumption because reported consumption rates are almost 100%.

4.5.2. Morbidity

We use several indicators to capture short-term health conditions and healthcare utilization: (a) illness-related school absence in the past month (binary), (b) illness frequency in the past month (count), (c) outpatient visits in the past month (count), (d) outpatient visits over the past year (count), and (e) hospitalization due to illness during the past year (binary). Children aged ten and older report this information themselves, while caregivers report for younger children.

Because illness incidence varies by age and sex, we standardize each morbidity indicator following Hoynes et al. (2016) as well as construct a composite morbidity index using inverse covariance weights following Anderson (2008). Details are in Supplementary Part B.

4.6. Sample attrition

The CFPS is an unbalanced panel because not all individuals are successfully followed in every wave. On average, children are observed in about three of the six survey waves between 2010 and 2018, with similar coverage across treatment and control groups. Geographic mobility is not common. Only 2.6% of child-wave observations involve a change in county of residence, and moving from NIP to non-NIP counties is rare. Thus, migration is unlikely to substantially change the composition of treatment and control groups over time.

A more important concern is whether attrition is related to NIP exposure or nutritional status. We test this using linear probability models and find that NIP exposure does not predict higher attrition. We likewise find no evidence that nutritional status is associated with attrition. Supplementary Part C reports the full attrition analysis.

5. Methods

5.1. Identification strategy

Our identification strategy exploits quasi-experimental variation in the timing of first NIP exposure at the individual level. This variation has two sources. First, counties implemented the NIP in different years. Second, children within the same county entered compulsory education in different years because they belong to different birth cohorts. These two sources of variation allow us to use a difference-in-differences (DID) model to compare children exposed to the NIP with rural children who had not yet received or never received the intervention during the study period. The key identifying assumption is that, conditional on fixed effects and covariates, treated and control children would have followed parallel health trends in the absence of the NIP.

We begin with a standard two-way fixed effects (TWFE) model:

$$Y_{it} = \alpha_0 + \alpha_1 NIP_{it} + X_{it}\gamma + \mu_i + \delta_{pt} + \theta_{ct} + \varepsilon_{it} \tag{1}$$

Here, Y_{it} denotes the health outcomes of child i in year t. NIP_{it} equals 1 if the child is exposed to the NIP in year t. The coefficient α_1 captures the average treatment effect. The vector (X_{it}) includes individual, household, and village characteristics, including individual ethnicity, parental education, family size, per capita household income, access to healthcare facility and pharmacy, and supply of piped drinking water. Because village information is collected in 2010, we interact these variables with year dummies. Individual fixed effects (μ_i) absorb time-invariant heterogeneity, such as genetics. Province-by-year fixed effects (δ_{pt}) capture province-specific shocks. Birth-cohort-by-year fixed effects (θ_{ct}) account for shocks common to children born in the same year. ε_{it} is the error term and standard errors are clustered at the county level.

TWFE estimators may be biased under staggered treatment adoption (Goodman-Bacon, 2021). Following de Chaisemartin and D'Haultfœuille (2020), we assess the extent of negative weighting in our setting and find that negative weights account for 0.54% of total weight mass, suggesting limited bias. We nevertheless report TWFE estimates alongside our preferred specification for transparency.

Our preferred estimator is the stacked DID approach developed by Cengiz et al. (2019) and Baker et al. (2022). For each treatment cohort defined by the year of first NIP exposure, we pair treated children with all never-treated rural children and then stack the resulting sub-datasets and estimate Eq. (1). Because each treated cohort is compared to never-treated children, the stacked estimator avoids the negative-weighting problem of TWFE DID models.

To examine dynamic treatment effects and test the parallel trends assumption, we estimate a stacked event study specification:

$$Y_{it} = \beta_0 + \sum_{k\neq-1}\beta_k 1\{t-T_i=k\} + X_{it}\gamma + \mu_i + \delta_{pt} + \theta_{ct} + \varepsilon_{it} \tag{2}$$

where T_i denotes the first year that child i receives the NIP. The indicator $1\{t-T_i=k\}$ identifies event time relative to first exposure, with $k=-1$ (the year immediately before treatment) as the omitted period. The pre-treatment coefficients ($k<-1$) test the parallel trends assumption. Statistically insignificant estimates would indicate that treated and control children followed similar health trends before NIP exposure and also rule out the concern of anticipation effects. The post-treatment coefficients ($k\geq 0$) reveal the dynamic treatment effects over time.

5.2. Testing for growth recovery

We are particularly interested in whether the NIP generates larger improvements among children with poorer nutritional status. We construct two measures of baseline nutritional status. The primary measure is baseline stunting, based on pre-treatment HAZ observations. When HAZ measurements before age six are available, we use their median value. Otherwise, we use the median of the child's two earliest HAZ observations. For children in the treatment group, all observations used to construct baseline HAZ must occur before the first year of NIP exposure. For children in the control group, we use the two earliest HAZ observations. We classify a child as stunted at baseline if this measure is below -2. We then re-estimate the stacked event study (Eq. (2)) separately for children with poorer and better nutritional status.

For robustness checks, our second measure classifies children according to whether they were ever observed to be stunted between 2010 and 2018.

We also interact NIP exposure with the nutritional status indicator in a full-sample regression to test whether treatment effects differ significantly across groups. To complement these analyses, we also estimate quantile regressions that allow the NIP effect to vary across the 10th to 90th percentiles of the HAZ distribution.

5.3. Early-life health investments and later nutritional interventions

We examine whether exposure to the NCMS during the first 1000 days of life shapes the effects of later NIP exposure. The staggered rollout of the NCMS and variation in children's birth cohorts generate differences in early-life exposure to healthcare services. We interact NIP exposure with early-life NCMS exposure ($EarlyNCMS_i$):

$$\begin{aligned} Y_{it} = {} & \beta_0 + \sum_{k\neq-1}\beta_k 1\{t-T_i=k\} + \sum_{k\neq-1}\varphi_k[1\{t-T_i=k\}\times EarlyNCMS_i] \\ & + X_{it}\gamma + \mu_i + \delta_{pt} + \theta_{ct} + \varepsilon_{it} \end{aligned} \tag{3}$$

The coefficients φ_k capture the additional effect of NIP exposure among children who received NCMS early in life. This specification also includes interactions between the NCMS indicator and year dummies to account for health trends associated with NCMS exposure.

Eq. (3) allows a triple-difference parallel trends test. The interaction coefficients φ_k for pre-treatment periods ($k<0$) indicate whether the health gap between children with and without early-life NCMS exposure was already changing before NIP exposure began. Statistically insignificant estimates would support that the estimated interaction effects are not driven by pre-existing differential trends.

6. Results

This section presents the main findings. First, we report the average treatment effects of the NIP and how these effects evolve with continued exposure. We also assess the robustness of the identification strategy. Then, we investigate whether the NIP benefits children with poorer nutritional status more. Next, we examine whether early-life exposure to the NCMS affects the effects of the NIP. Finally, we test the mechanisms through which the NIP impacts child health.

6.1. Baseline estimation

Mean effects of NIP exposure on nutritional status

Table 2 presents estimated effects of NIP exposure on child anthropometrics. Each column reports results from both the TWFE and the stacked DID specifications using Eq. (1). Both estimators yield effects with consistent signs and statistical significance across outcomes. The stacked DID estimates are slightly larger in magnitude. Because the stacked DID approach relies on never-treated units as controls, we focus on these estimates for interpretation.

Panel A reports effects on undernutrition. NIP exposure increases HAZ by 0.29 standard deviations and reduces stunting by 14.6 percentage points. During 2010–2018, mean HAZ among treated children increased from −1.51 to −0.71, and the stunting rate declined from 42% to 13%. The NIP may account for a significant share of this improvement. The effect on thinness is small and statistically insignificant.

These findings indicate that school feeding can improve child growth and reduce chronic undernutrition during the school-age years. The results are consistent with previous evaluations of SFPs in China and India, which report HAZ gains of about 0.2–0.4 standard deviations and substantial reductions in stunting (Shrinivas et al., 2025; Singh et al., 2014; Su et al., 2024; Wang et al., 2023). Evidence on thinness is mixed, and our null findings are consistent with results from Ghana and Thailand (Gelli et al., 2019; Pongutta et al., 2023).

Table 2
Impact of NIP exposure on child anthropometric outcomes.

Panel A: Undernutrition outcomes			
	(1) HAZ	(2) Stunting	(3) Thinness
TWFE DID	0.231**	−0.088***	0.003
	(0.098)	(0.028)	(0.036)
Stacked DID	0.290***	−0.146***	0.009
	(0.095)	(0.030)	(0.032)
Panel B: Overweight and obesity outcomes			
	(4) BAZ	(5) Overweight	(6) Obesity
TWFE DID	−0.308**	−0.069**	−0.057**
	(0.151)	(0.034)	(0.022)
Stacked DID	−0.429***	−0.096**	−0.090***
	(0.144)	(0.040)	(0.027)
Controls	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
Province × Year FE	Yes	Yes	Yes
Birth cohort × Year FE	Yes	Yes	Yes
Observations	13,099	13,099	13,099

Notes: Each cell reports the estimated coefficient on the NIP exposure dummy from a separate regression (Eq. (1)). Standard errors, clustered at the county level, are reported in parentheses. The thinness analysis uses 11,054 observations. ** $p < 0.05$, *** $p < 0.01$.

Panel B presents effects on overnutrition. NIP exposure reduces BAZ by 0.43, lowers the probability of overweight by 9.6 percentage points, and lowers the probability of obesity by 9.0 percentage points. These findings suggest that the NIP improves nutritional status without creating a trade-off between reducing undernutrition and preventing overnutrition. This is particularly relevant in rural China, where undernutrition and overnutrition coexist. We explore the potential mechanisms in Section 6.6.

Previous evidence regarding overnutrition is relatively limited. Many studies in LMICs report insignificant effects of SFPs on overweight and obesity (Alderman et al., 2024). Studies from upper-middle-income and high-income countries show comparable results. SFPs in Brazil, Japan, and England have been shown to reduce overweight and obesity, particularly among socioeconomically disadvantaged children (Boklis-Berer et al., 2021; Holford and Rabe, 2024; Maruyama and Nakamura, 2025). Our estimates are larger in magnitude than these studies, possibly due to the higher baseline prevalence of overnutrition in rural China.

Subgroup analysis

Further, we compare NIP effects across gender groups and by household per capita income and parental education. As shown in Supplementary Table A4, estimated effects tend to be larger among girls, children from lower-income households, and children whose parents have lower levels of education. These groups also have lower mean HAZ than their counterparts.

These results suggest that the benefits of the NIP may be concentrated among children facing greater nutritional disadvantages. This also implies that the NIP may reduce inequalities in child health. We examine this hypothesis more directly in Section 6.4 by analyzing treatment effect heterogeneity according to children's baseline nutritional status.

6.2. Dynamic effects and dose–response

Event study

Fig. 2 presents stacked event study estimates for HAZ, stunting, and thinness based on Eq. (2). The coefficients for pre-treatment periods (from −6 to −2) are close to zero and statistically insignificant, suggesting no evidence of differential pre-treatment trends or anticipation effects.

The post-treatment coefficients indicate that NIP benefits accumulate over time. Panel (a) shows that gains in HAZ emerge after one year of exposure and continue to increase thereafter, reaching approximately 0.4–0.5 standard deviations after six years. This pattern is consistent with the cumulative nature of nutritional investments and with the dynamic effects of SFPs in other LMICs (Chakrabarti et al., 2021). Panel (b) reveals a similar pattern for stunting. The estimated effects become increasingly negative over time. Panel (c) shows no statistically significant effects on thinness.

Supplementary Fig. A6 presents stacked event study estimates for BAZ, overweight, and obesity. The parallel trends assumption holds across all three regressions. Post-treatment effects become increasingly negative, indicating that longer exposure is associated with larger reductions in overnutrition.

Dose-response analysis

The event study estimates suggest that effects accumulate with continued exposure. To examine this relationship more directly, we replace the binary treatment indicator with continuous measures of program exposure, capturing duration and intensity. Since the stacked DID approach is not applicable to continuous treatment specifications, we estimate TWFE models. Table 3 reports the results. For reference, column (1) reproduces the baseline estimate based on the binary treatment indicator.

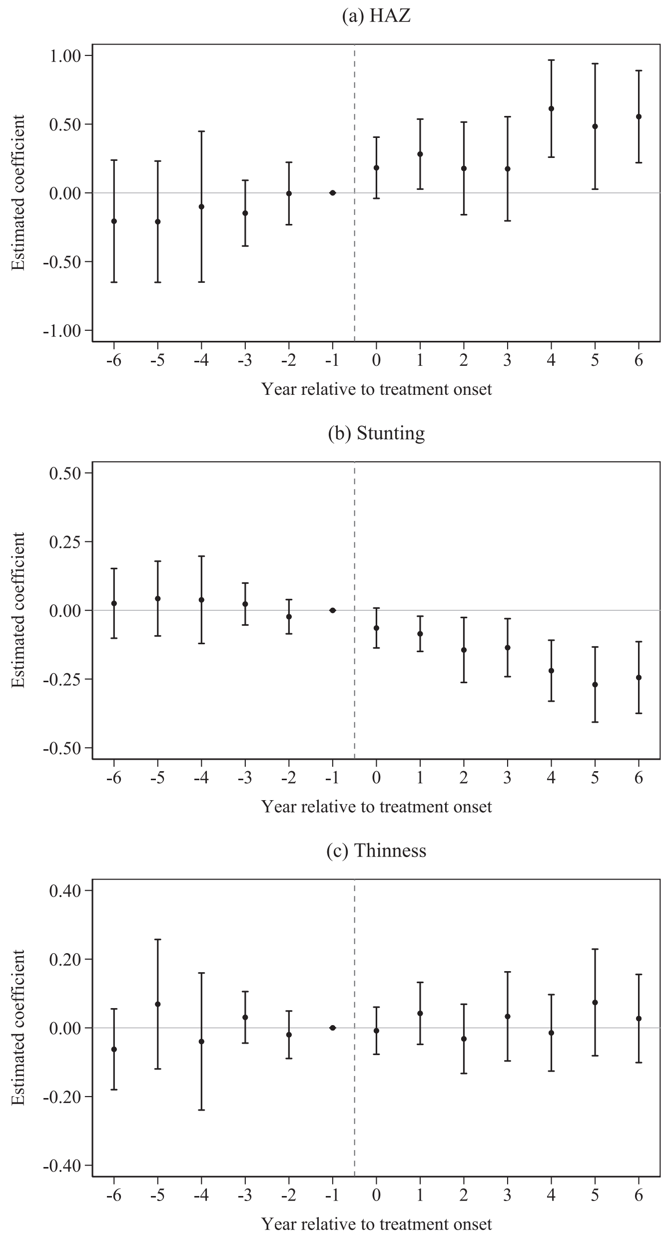

Fig. 2. Dynamic effects of NIP exposure on undernutrition outcomes. *Notes*: This figure reports coefficient estimates from Eq. (2) using the stacked event study specification. The sample includes 13,099 observations for the HAZ and stunting analyses and 11,054 observations for the thinness analysis. Error bars indicate 95% confidence intervals. Period 0 denotes the first year of NIP exposure.

Column (2) shows that each additional year of NIP exposure increases HAZ by 0.07 and reduces stunting by 3.3 percentage points. The binned specification in column (3) shows that, for HAZ, the estimated effect rises from 0.22 among children exposed for 1–3 years to 0.35 among those exposed for 4–6 years. The reductions in stunting are also larger among children with longer exposure durations. Column (4) examines treatment intensity using cumulative per-student NIP subsidies, measured in thousands of 2011 CNY (about USD 154). An additional 1000 CNY of cumulative investment increases HAZ by 0.11 and reduces stunting by about 5 percentage points. These results suggest that both the duration and intensity of exposure contribute to the observed improvements in child growth.

To assess practical significance, we translate the HAZ estimates into centimeters (cm). According to the WHO 2007 growth reference, the height standard deviation at our sample mean age of 9.5 years is about 5.9 cm. The back-of-the-envelope calculations in Supplementary Table A5 suggest that a child with average NIP exposure gains around 1.7 cm in height relative to an unexposed child. Each additional year of exposure adds roughly 0.4 cm, and children exposed for 4–6 years gain nearly 2 cm.

Table 3
Impact of duration and intensity of NIP exposure on HAZ and stunting.

	Binary	Duration (continuous)	Duration (binned)	Investment intensity
Panel A: HAZ	(1)	(2)	(3)	(4)
NIP exposure (=1)	0.231**			
	(0.098)			
Years exposed		0.074***		
		(0.026)		
1–3 years			0.215**	
			(0.101)	
4–6 years			0.345**	
			(0.144)	
Cumulative investment (1000 CNY, 2011 prices)				0.113***
				(0.042)
Panel B: Stunting				
	(5)	(6)	(7)	(8)
NIP exposure (=1)	−0.088***			
	(0.028)			
Years exposed		−0.033***		
		(0.008)		
1–3 years			−0.078***	
			(0.027)	
4–6 years			−0.155***	
			(0.048)	
Cumulative investment (1000 CNY, 2011 prices)				−0.053***
				(0.013)
Controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Province × Year FE	Yes	Yes	Yes	Yes
Birth cohort × Year FE	Yes	Yes	Yes	Yes
Observations	13,099	13,099	13,099	13,099

Notes: Each column reports estimates from a separate TWFE regression (Eq. (1)). In the duration-bin specifications (columns 3 and 7), the reference category is years exposed = 0, which includes both never-treated and not-yet-treated children. Standard errors, clustered at the county level, are reported in parentheses. ** $p < 0.05$, *** $p < 0.01$.

The estimated annual gain of 0.4 cm is consistent with existing evidence. A meta-analysis of randomized controlled trials of SFPs in LMICs reports an average annual height gain of 0.32 cm (Wang et al., 2021), while some programs suggest larger effects. For example, a program in poor regions of Guyana increased child height by about 0.8 cm within one year (Ismail et al., 2012).

The cumulative gains are also meaningful from a policy perspective. The rural–urban height gap among school-age children in China is about 4 cm (Supplementary Fig. A1). Our estimates imply that six years of NIP exposure may close nearly half of this gap.

6.3. Placebo test and robustness checks

One concern is that the estimated effects may reflect other contemporaneous policies or broader time trends rather than the NIP. To assess this possibility, we perform a falsification test using urban children born between 1996 and 2012 and aged 2–16, a population that was never exposed to the program. Following the same procedure used for the rural sample, we assign placebo treatment dates to urban children and estimate the stacked event study specification. If the main estimates capture factors unrelated to the NIP, similar effects should also appear in the placebo sample. The estimated coefficients are small and statistically insignificant in both pre- and post-treatment periods (Supplementary Fig. A7). This suggests that our main results are unlikely to be driven by contemporaneous policies or broader trends.

In addition, we conduct several robustness checks, including permutation tests, alternative staggered DID estimators developed by Wooldridge (2025) and Sun and Abraham (2021), sensitivity analyses proposed by Rambachan and Roth (2023), and tests addressing data quality, migration, and measurement concerns. Across all tests, the estimated effects remain stable. Detailed results are reported in Supplementary Information D.

6.4. Heterogeneity by initial nutritional status

We next examine whether the benefits of the NIP are concentrated among children with poorer initial nutritional status. We re-estimate the stacked event study specification in Eq. (2) separately for children classified as stunted and non-stunted using the definitions described in Section 5.2. Fig. 3 reports the results. In all regressions, the pre-treatment coefficients are statistically insignificant, supporting the parallel trends assumption.

Panel (a) classifies children according to baseline stunting status. Among children who were stunted prior to treatment, the NIP effects on HAZ emerge within the first year of exposure and increase steadily over time, reaching about 1.0 standard deviation after five to six years. The effects on HAZ among non-stunted children are small during the post-treatment period. These results suggest that the benefits of school feeding are concentrated among children with substantial growth deficits. Panel (b), which classifies children according to whether they were ever observed to be stunted during the study period, shows consistent results.

Supplementary Table A6 reports additional evidence from full-sample regressions that interact NIP exposure with indicators of nutritional disadvantage. The interaction terms are positive and statistically significant for HAZ and negative and significant for stunting, confirming that NIP effects are larger among children with poorer initial nutritional status.

Fig. 4 further examines heterogeneity across the HAZ distribution using quantile regressions. The estimated effects are largest at the lowest quantiles, e.g., 0.58 at the 10th percentile and 0.39 at the 30th percentile. The effects decline and become statistically insignificant at higher quantiles. These findings confirm that the NIP primarily benefits children with the most severe growth deficits.

These findings echo the subgroup results reported in Section 6.1, which show larger gains among socioeconomically disadvantaged children, who have lower HAZ scores. More broadly, our results provide evidence that school feeding can promote growth recovery during the school-age years. They also align with a growing body of research suggesting that nutritional interventions delivered beyond early childhood may generate particularly large benefits for children who have experienced growth failure (Roberts and Stein, 2017).

6.5. Heterogeneity by early-life NCMS exposure

Before examining whether early-life exposure to the NCMS influences the potential for growth recovery, we assess its direct effects on child growth. Using a cohort DID analysis reported in Supplementary Part E, we find that full NCMS exposure during the first 1000 days reduces stunting by 5 percentage points but does not affect HAZ. This pattern is plausible because the NCMS expands access to healthcare services rather than providing direct nutritional support.

Next, we examine the interaction of NIP and early-life NCMS exposure, as modeled in Eq. (3). Fig. 5 presents stacked event study estimates on HAZ and stunting. Panel (a) shows that children exposed only to the NIP and those exposed to both the NIP and the NCMS experience significant improvements in HAZ. Panel (b) reports the interaction effects. The estimated interaction coefficients (φ_k) are small and insignificant, indicating that NCMS exposure does not amplify the average height gains generated by school feeding. The pre-treatment coefficients are

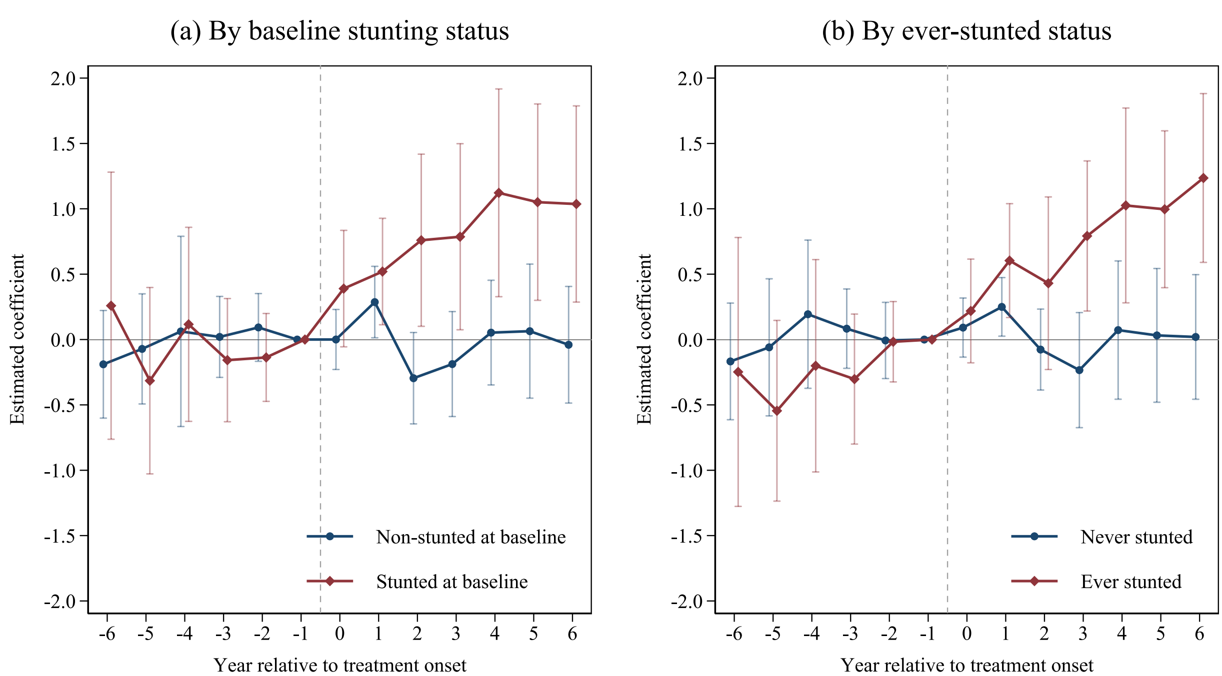

Fig. 3. Event-study estimates by nutritional status. *Notes*: This figure presents stacked event study estimates from Eq. (2) of the effect of NIP exposure on HAZ, estimated separately by children's nutritional status. Panel (a) classifies treatment and control children by baseline stunting status. Panel (b) classifies children according to whether they were ever observed to be stunted. Error bars represent 95% confidence intervals. Period 0 denotes the first year of NIP exposure.

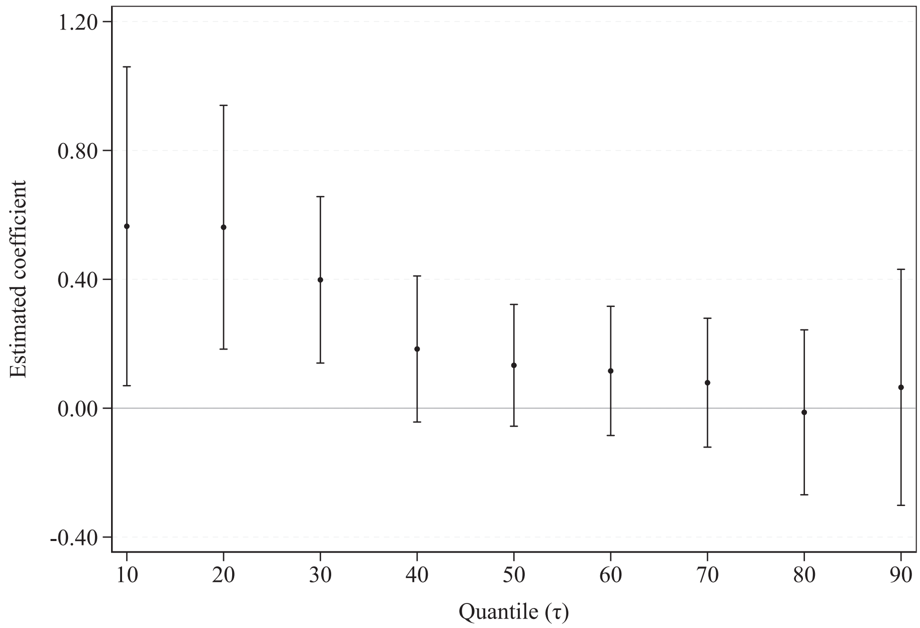

Fig. 4. Quantile regression. *Notes*: This figure presents the results of quantile regressions estimating the impact of NIP exposure on the distribution of HAZ, estimated at deciles from the 10th to 90th percentile. All specifications include individual, province-by-year, and birth-cohort-by-year fixed effects. Control variables include individual ethnicity, parental education, family size, per capita household income, and 2010 village characteristics. Standard errors are clustered at the county level. Error bars represent 95% confidence intervals.

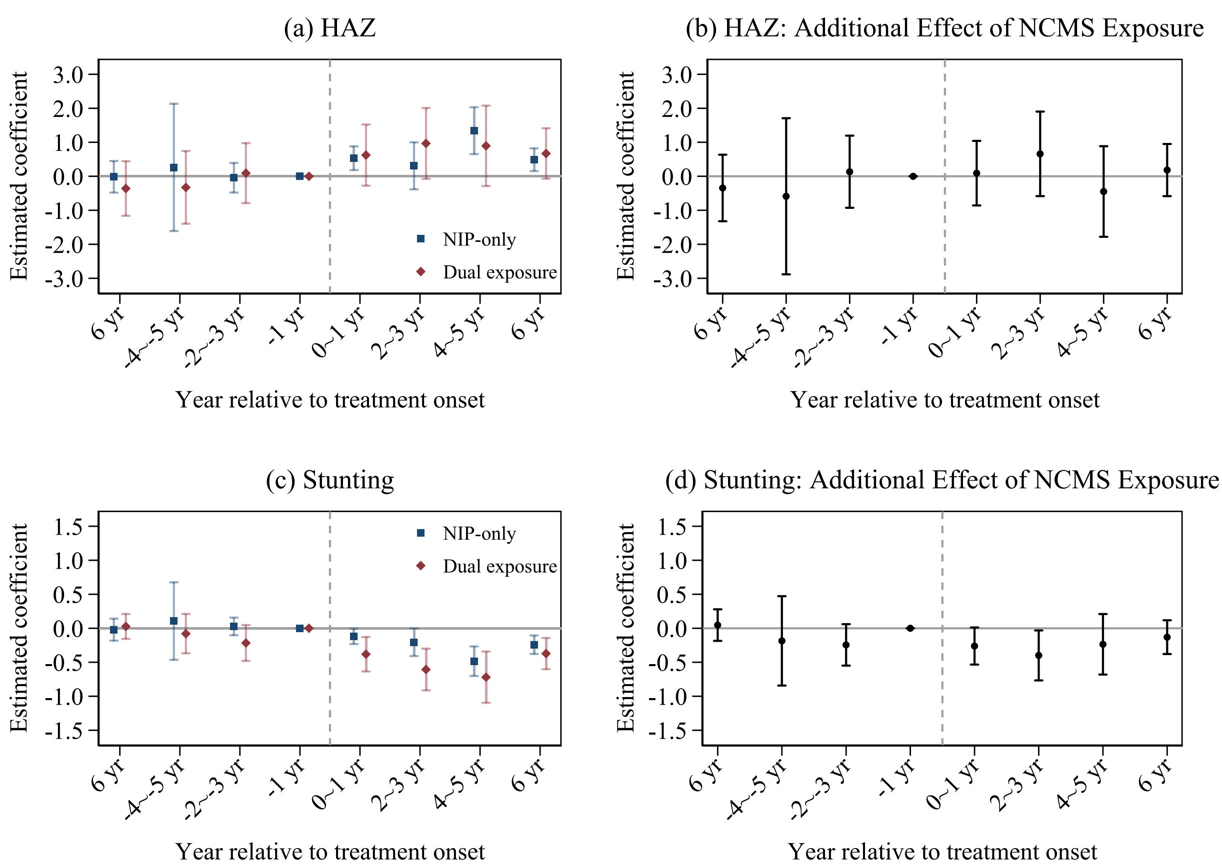

Fig. 5. Dynamic effects of the NIP by NCMS exposure (implemented before birth). *Notes*: This figure shows stacked event study coefficients from Eq. (3) using the full sample. In Panels (a) and (c), the blue line represents children with only NIP exposure, while the red line represents children with dual exposure. Panels (b) and (d) show the additional effect of NIP for children with early-life NCMS exposure relative to those without such exposure. Standard errors are clustered at the county level. Error bars indicate 95% confidence intervals. Period 0 denotes the first year of NIP exposure.

insignificant, supporting the parallel trends assumption.

Panels (c) and (d) reveal a different pattern for stunting. Although stunting declines following NIP exposure in both groups, the reductions are larger among children exposed to the NCMS early in life. The interaction effects are negative and statistically significant, indicating that exposure to both programs generates additional reductions in stunting. Supplementary Fig. A8 reports similar results using an alternative definition of NCMS exposure that classifies children as exposed if the NCMS was introduced at any point before age two.

These results mean that the interaction primarily affects children near the stunting threshold, rather than improving linear growth overall. Early-life healthcare does not increase the average height response to school feeding. Instead, by mitigating the impact of early health deficits and improving children's capacity to utilize nutrients, it may place disadvantaged children closer to the stunting threshold. Consequently, these children are more likely to experience sufficient growth from subsequent NIP exposure to recover from stunting.

6.6. Mechanism analysis

6.6.1. Dietary intake

Supplementary Fig. A9 presents stacked event study estimates of the effects of NIP exposure on the consumption of six food categories. The most pronounced dietary change is a reduction in the consumption of fried and puffed foods. We do not find significant changes in the consumption of protein-rich foods, including meat, milk, eggs, and nuts. The decline in fried and puffed food consumption suggests that school feeding may partially substitute for energy-dense foods, consistent with the reductions in overweight and obesity.

The insignificant effects on protein-rich foods do not necessarily mean that the NIP fails to improve dietary quality. Three factors likely contribute. First, dietary information is available only through 2014, when the purchasing power of the NIP subsidy remained low in some provinces (Supplementary Fig. A3). Second, although the Ministry of Education established detailed standards for food procurement, cooking, and nutritional balance, only about half of the schools in the pilot counties had well-equipped canteens in 2012 (Ministry of Education of China, 2012). These schools may provide basic food items rather than nutritionally balanced meals in the early program years. Third, the CFPS records only binary indicators of weekly food consumption and cannot capture changes in portion size or nutrient composition. Consumption rates for some foods are already high (meat 80%, eggs 69%), resulting in limited within-individual variation under individual fixed effects. When we instead use county fixed effects, the estimates additionally suggest increased meat consumption and reduced pickled food consumption (Supplementary Fig. A10). However, these estimates should be interpreted cautiously because they are more susceptible to unobserved confounding.

6.6.2. Morbidity

We examine whether NIP exposure affects child morbidity. Supplementary Table A7 reports stacked DID estimates for a composite morbidity index and five individual indicators. NIP exposure significantly reduces the morbidity index by 0.20 standard deviations. The effects are concentrated in illness frequency and outpatient healthcare utilization. Effects on illness-related school absence and hospitalization are also negative but insignificant.

Supplementary Fig. A11 presents the event study estimates. Across all outcomes, the pre-treatment coefficients are insignificant. The post-treatment coefficients become increasingly negative over time, particularly for the composite morbidity index, suggesting that the benefits of the NIP accumulate with continued exposure. The dynamic pattern also matches how treatment effects evolve on HAZ and stunting, suggesting that reduced morbidity is one channel through which the NIP contributes to improvements in child growth.

7. Discussion and conclusion

School feeding has become the most widespread child health intervention in the world. Using nationally representative panel data from China between 2010 and 2018, this study examines whether a large-scale school feeding program can improve child health beyond the first 1000 days of life. We find that exposure to the NIP increases height-for-age and reduces stunting. These benefits accumulate with continued exposure and are accompanied by reductions in overweight and obesity. Mechanism analyses suggest that improvements in diets and reductions in morbidity likely mediate these effects.

Our findings contribute to a debate regarding the reversibility of early growth deficits. A common view is that the first 1000 days constitute a critical period after which opportunities for growth recovery become increasingly limited (see Attanasio, 2026, for a recent review). Our results suggest a more nuanced picture. While early-life interventions are important, the school years can also be a meaningful window for improving child growth. The largest benefits of the NIP accrue to children with the poorest nutritional status. Children who were stunted prior to treatment experience larger improvements in HAZ and larger reductions in stunting. Similar patterns emerge among children from socioeconomically disadvantaged households. These findings indicate that school feeding can promote growth recovery and help reduce health disparities that emerge earlier in life.

Our study also contributes to the literature on the double burden of malnutrition. Most studies of SFPs in LMICs focus on undernutrition. We show that the NIP reduces stunting while simultaneously lowering overweight and obesity. The dietary evidence suggests that school meals may partly replace energy-dense foods. School feeding need not involve a trade-off between reducing undernutrition and preventing excess calorie intake. In settings where both forms of malnutrition coexist, well-designed SFPs may help address multiple nutritional challenges.

Beyond dietary channels, we find that NIP exposure reduces morbidity, particularly illness frequency and outpatient healthcare utilization. These reductions accumulate over time in a pattern consistent with the gradual improvements in HAZ, supporting reduced morbidity as an additional pathway through which school feeding contributes to child growth. Lower illness rates may also improve school attendance. Consequently, reduced morbidity represents an important mechanism linking school feeding to gains in child growth and, potentially, long-term human development.

Another contribution involves the interaction between interventions delivered at different life stages. We find that children exposed to both the NCMS and the NIP are more likely to recover from stunting. Hence, although SFPs can promote growth recovery among children who missed earlier developmental opportunities, a favorable early-life health environment further increases the likelihood that these children benefit from school feeding.

These findings have policy implications. First, while the first 1000 days are important for child development, they do not represent the end of opportunities for intervention. Investments during the school-age period can generate meaningful health improvements among children with the greatest initial disadvantages. Second, school feeding programs can contribute to addressing both undernutrition and overnutrition when meals are appropriately designed. Third, school feeding should not be viewed as a substitute for early-life health investments. Interventions delivered at different stages may impact different aspects of health. We advocate for a life-course approach to child development that coordinates nutrition and health policies.

Several limitations should also be acknowledged. First, we do not capture changes in food quantity and quality driven by the NIP. More detailed dietary measures, such as 24-h dietary recalls, would allow a more precise assessment of dietary mechanisms. Second, while we identify an interaction between early-life NCMS exposure and later school feeding and discuss plausible mechanisms, we do not directly test which mechanisms drive this relationship. Further interdisciplinary research in nutrition and child development is needed. Third, it remains unclear whether the documented height gains persist into adulthood or translate into longer-term health and economic outcomes.

The external validity of our findings should also not be overstated. China faces the coexistence of undernutrition and rapidly rising overnutrition, and the NIP employs a program design that differs from that of many SFPs elsewhere. More comparative research is needed across countries with different nutritional conditions and program designs.

Nevertheless, our findings point to a broader implication. Well-designed SFPs can improve child health beyond early childhood, particularly among children facing the greatest nutritional and socioeconomic disadvantages. In a world where nutritional inequalities remain pervasive and social protection systems face growing pressures, school feeding is a potentially powerful tool for promoting healthier and more equitable child development.

CRediT authorship contribution statement

Zhen Liu: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Zuhui Huang:** Supervision, Project administration, Funding acquisition, Conceptualization.

Ethics declaration

Written informed consent to take part in the study and to publish the article has been obtained from all participants or their legal representatives. The privacy rights of participants have been observed.

This study was performed in compliance with relevant laws, regulatory frameworks and guidelines where the research took place. This study was approved by the Institutional Review Board of the German Association for Experimental Economic Research. (Approval No. ChPmKR6P).

Declaration of competing interest

The authors declare no competing interest.

Acknowledgements

The first author acknowledges financial support from the China Scholarship Council (Grant No. 202106320115), the Social Science Foundation of Liaoning Province (Grant No. L25CGL018), and the Social Science Foundation of Jiangsu Province (Grant No. 25GLC014).

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.foodpol.2026.103190.

References

Abramovsky, L., Augsburg, B., Jervis, P., Malde, B., Phimister, A., 2025. Complementarities in the production of child health. J. Hum. Cap. 19, 572–613. https://doi.org/10.1086/735106.

Adhvaryu, A., Molina, T., Nyshadham, A., Tamayo, J., 2023. Helping children catch up: early life shocks and the PROGRESA experiment. Econ. J. 134, 1–22. https://doi.org/10.1093/ej/uead067.

Alderman, H., Behrman, J.R., McGregor, S.G., Boo, F.L., Urzua, S., 2014. Economic perspectives on integrating early child stimulation with nutritional interventions. Ann. N. Y. Acad. Sci. 1308, 129–138. https://doi.org/10.1111/nyas.12331.

Alderman, H., Bundy, D., Gelli, A., 2024. School meals are evolving: has the evidence kept up? World Bank Res. Obs. 39, 159–176. https://doi.org/10.1093/wbro/lkad012.

Anderson, M.L., 2008. Multiple inference and gender differences in the effects of early intervention: a reevaluation of the Abecedarian, Perry Preschool, and Early Training projects. J. Am. Stat. Assoc. 103, 1481–1495. https://doi.org/10.1198/016214508000000841.

Attanasio, O., 2026. The first 1000 days and beyond: The process of child development. J. Econ. Lit., forthcoming. https://doi.org/10.3386/w34651.

Babiarz, K.S., Miller, G., Yi, H., Zhang, L., Rozelle, S., 2010. New evidence on the impact of China's New Rural Cooperative Medical Scheme and its implications for rural primary healthcare: Multivariate difference-in-difference analysis. BMJ 341, c5617. https://doi.org/10.1136/bmj.c5617.

Baker, A.C., Larcker, D.F., Wang, C.C.Y., 2022. How much should we trust staggered difference-in-differences estimates? J. Financ. Econ. 144, 370–395. https://doi.org/10.1016/j.jfineco.2022.01.004.

Boklis-Berer, M., Rauber, F., Azeredo, C.M., Levy, R.B., Louzada, M.L.D.C., 2021. The adherence to school meals is associated with a lower occurrence of obesity among Brazilian adolescents. Prev. Med. 150, 106709. https://doi.org/10.1016/j.ypmed.2021.106709.

Bourke, C.D., Jones, K.D.J., Prendergast, A.J., 2019. Current understanding of innate immune cell dysfunction in childhood undernutrition. Front. Immunol. 10, 1728. https://doi.org/10.3389/fimmu.2019.01728.

Case, A., Lubotsky, D., Paxson, C., 2002. Economic status and health in childhood: the origins of the gradient. Am. Econ. Rev. 92, 1308–1334. https://doi.org/10.1257/000282802762024520.

Cengiz, D., Dube, A., Lindner, A., Zipperer, B., 2019. The effect of minimum wages on low-wage jobs. Q. J. Econ. 134, 1405–1454. https://doi.org/10.1093/qje/qjz014.

Chakrabarti, S., Scott, S.P., Alderman, H., Menon, P., Gilligan, D.O., 2021. Intergenerational nutrition benefits of India's national school feeding program. Nat. Commun. 12, 4248. https://doi.org/10.1038/s41467-021-24433-w.

de Chaisemartin, C., D'Haultfœuille, X., 2020. Two-way fixed effects estimators with heterogeneous treatment effects. Am. Econ. Rev. 110, 2964–2996. https://doi.org/10.1257/aer.20181169.

de Onis, M., Onyango, A.W., Borghi, E., Siyam, A., Nishida, C., Siekmann, J., 2007. Development of a WHO growth reference for school-aged children and adolescents. Bull. World Health Organ. 85, 660–667. https://doi.org/10.2471/BLT.07.043497.

Duan, X., Liang, Y., Peng, X., 2024. Free school meals and cognitive ability: evidence from China's student nutrition improvement plan. Health Econ. 33, 1480–1502. https://doi.org/10.1002/hec.4824.

Fang, G., Zhu, Y., 2022. Long-term impacts of school nutrition: evidence from China's school meal reform. World Dev. 153, 105854. https://doi.org/10.1016/j.worlddev.2022.105854.

Gelli, A., Aurino, E., Folson, G., Arhinful, D., Adamba, C., Osei-Akoto, I., Masset, E., Watkins, K., Fernandes, M., Drake, L., Alderman, H., 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, 1434–1442. https://doi.org/10.1093/jn/nxz079.

Georgiadis, A., Penny, M.E., 2017. Child undernutrition: opportunities beyond the first 1000 days. Lancet Public Health 2, e399.

Goodman-Bacon, A., 2021. Difference-in-differences with variation in treatment timing. J. Econom. 225, 254–277. https://doi.org/10.1016/j.jeconom.2021.03.014.

Guan, Z., He, Y., Shi, X., Zhang, C., 2025. The long-term impact of the nutrition improvement program on children's education outcomes: Empirical evidence from rural China. Food Policy 135, 102915. https://doi.org/10.1016/j.foodpol.2025.102915.

Hirvonen, K., 2013. Measuring catch-up growth in malnourished populations. Ann. Hum. Biol. 41, 67–75. https://doi.org/10.3109/03014460.2013.827239.

Holford, A., Rabe, B., 2024. Universal free school meals and children's bodyweight: Impacts by age and duration of exposure. J. Health Econ. 98, 102937. https://doi.org/10.1016/j.jhealeco.2024.102937.

Hoynes, H., Schanzenbach, D.W., Almond, D., 2016. Long-run impacts of childhood access to the safety net. Am. Econ. Rev. 106, 903–934. https://doi.org/10.1257/aer.20130375.

Hsiao, W., Li, M., Zhang, S., 2014. Universal health coverage: The case of China. United Nations Research Institute for Social Development, Geneva. https://www.econstor.eu/handle/10419/148725.

Huang, W., Liu, H., 2023. Early childhood exposure to health insurance and adolescent outcomes: evidence from rural China. J. Dev. Econ. 160, 102925. https://doi.org/10.1016/j.jdeveco.2022.102925.

Ismail, S., Borja-Vega, C., Demas, A., Jarvis, E., 2012. Guyana's hinterland and community-based school feeding programme. World Bank, Washington, DC. https://documents.worldbank.org/en/publication/documents-reports/documentdetail/690761468031534184.

Liang, X., Hu, Q., Hou, X., Xu, J., 2025. The National Nutrition Improvement Program and the equity of educational opportunities: evidence from rural China. Appl. Econ. 57, 2299–2315. https://doi.org/10.1080/00036846.2024.2323548.

Maruyama, S., Nakamura, S., 2025. Wholesome lunch to the whole classroom: short- and longer-term effects on early teenagers' weight. Health Econ. 34, 1255–1273. https://doi.org/10.1002/hec.4959.

Millward, D.J., 1995. A protein-stat mechanism for regulation of growth and maintenance of the lean body mass. Nutr. Res. Rev. 8, 93–120. https://doi.org/10.1079/nrr19950008.

Ministry of Education of China, 2021. A look at how programs to improve nutrition can also boost a generation's overall physical fitness. http://www.moe.gov.cn/jyb_xwfb/s5147/202112/t20211224_589891.html. (Accessed 2 September 2026).

Ministry of Education of China, 2012. Interim measures for the management of canteens in rural compulsory education schools. http://www.moe.gov.cn/jyb_xwfb/moe_1946/s6197/201206/t20120614_137693.html. (Accessed 2 September 2026).

National Health Commission of China, 2018. Reply to proposal No. 3626 of the first session of the 13th National People's Congress. https://www.nhc.gov.cn/wjw/jiany/201901/4299cbd02c5f4d609501dd5d82f3da61.shtml. (Accessed 2 September 2026).

Pongutta, S., Ferguson, E., Davey, C., Tangcharoensathien, V., Limwattananon, S., Borghi, J., Wong, C.K.H., Lin, L., 2023. The impact of a complex school nutrition intervention on double burden of malnutrition among Thai primary school children: a 2-year quasi-experiment. Public Health 224, 51–57. https://doi.org/10.1016/j.puhe.2023.08.023.

Prendergast, A.J., Humphrey, J.H., 2014. The stunting syndrome in developing countries. Paediatr. Int. Child Health 34, 250–265. https://doi.org/10.1179/2046905514y.0000000158.

Prentice, A.M., Ward, K.A., Goldberg, G.R., Jarjou, L.M., Moore, S.E., Fulford, A.J., Prentice, A., 2013. Critical windows for nutritional interventions against stunting. Am. J. Clin. Nutr. 97, 911–918. https://doi.org/10.3945/ajcn.112.052332.

Rambachan, A., Roth, J., 2023. A more credible approach to parallel trends. Rev. Econ. Stud. 90, 2555–2591. https://doi.org/10.1093/restud/rdad018.

Ren, J., Zheng, X., Smith, R., Fang, X., 2023. School feeding program and urban–rural inequality of child health: evidence from China. Agribusiness 39, 1399–1416. https://doi.org/10.1002/agr.21862.

Roberts, J.L., Stein, A.D., 2017. The impact of nutritional interventions beyond the first 2 years of life on linear growth: a systematic review and meta-analysis. Adv. Nutr. 8, 323–336. https://doi.org/10.3945/an.116.013938.

Shrinivas, A., Baylis, K., Crost, B., 2025. Food transfers and child nutrition: evidence from India's Public Distribution System. Am. Econ. J. Appl. Econ. 17, 161–207. https://doi.org/10.1257/app.20220505.

Singh, A., Park, A., Dercon, S., 2014. School meals as a safety net: an evaluation of the midday meal scheme in India. Econ. Dev. Cult. Change 62, 275–306. https://doi.org/10.1086/674097.

Su, D., Xie, H., Zhang, P., 2024. Nutrition and child development: Evidence from the student nutrition improvement program. SSRN Electron. J. https://doi.org/10.2139/ssrn.4708989.

Sun, L., Abraham, S., 2021. Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. J. Econom. 225, 175–199. https://doi.org/10.1016/j.jeconom.2020.09.006.

UNICEF, WHO, WBG, 2025. Levels and trends in child malnutrition: UNICEF/WHO/World Bank Group Joint Child Malnutrition Estimates. Key findings of the 2025 edition. World Health Organization, Geneva. https://www.who.int/publications/i/item/9789240112308.

Wang, D., Shinde, S., Young, T., Fawzi, W.W., 2021. Impacts of school feeding on educational and health outcomes of school-age children and adolescents in low- and middle-income countries: a systematic review and meta-analysis. J. Glob. Health 11, 04051. https://doi.org/10.7189/jogh.11.04051.

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, 102228. 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, H., Zhao, Q., Boswell, M., Rozelle, S., 2020. Can school feeding programs reduce malnutrition in rural China? J. Sch. Health 90, 56–64. https://doi.org/10.1111/josh.12849.

Wang, J., Hernandez, M.A., Deng, G., 2023. Large-scale school meal programs and student health: evidence from rural China. China Econ. Rev. 79, 101974. https://doi.org/10.1016/j.chieco.2023.101974.

Wang, J., Zhou, L., Yao, S., 2019. The impact of the nutrition improvement program on children's health in rural areas: evidence from China. Emerg. Mark. Finance Trade 58, 267–289. https://doi.org/10.1080/1540496x.2019.1706047.

Wang, L., Zhang, S., Hao, X., Peng, A., Rule, A., Wang, H., Rozelle, S., 2026. School feeding program and health outcomes among school-aged children: evidence from rural China. J. Sch. Health 96, e70118. https://doi.org/10.1111/josh.70118.

WHO, 2006. WHO child growth standards: Length/height-for-age, weight-for-age, weight-for-length, weight-for-height and body mass index-for-age: Methods and development. World Health Organization, Geneva. https://www.who.int/publications/i/item/924154693X.

Wooldridge, J.M., 2025. Two-way fixed effects, the two-way Mundlak regression, and difference-in-differences estimators. Empir. Econ. 69, 2545–2587. https://doi.org/10.1007/s00181-025-02807-z.

Zhao, C., Chen, B., Song, Z., 2024. School nutritious feeding and cognitive abilities of students in poverty: evidence from the nutrition improvement program in China. Child. Youth Serv. Rev. 159, 107519. https://doi.org/10.1016/j.childyouth.2024.107519.

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, 6459–6478. https://doi.org/10.1080/00036846.2022.2156472.

Zhou, L., Wang, J., Jiang, B., 2021. The impact of rural compulsory education nutrition improvement program on students' health. China Rural Surv. 2, 97–114 (in Chinese). https://zgncgc.ajcass.com/Magazine/Show/76919.

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, 101335. https://doi.org/10.1016/j.ehb.2023.101335.