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Does money matter for child nutrition? Exploration of a preschool nutrition program in rural South-Central China

Xinjie Shi [a], Kevin Chen [a,b,*], Chengfang Liu [c], Yanying Yu [a]

[a] China Academy for Rural Development, School of Public Affairs, Zhejiang University, Hangzhou, China
[b] International Food Policy Research Institute, Beijing Office, Beijing, China
[c] China Center for Agricultural Policy, School of Advanced Agricultural Sciences, Peking University, Beijing, China

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ABSTRACT

Objectives: The aim of this study was to examine the relationship between poverty and children's nutritional outcomes.
Methods: Drawing on a 2018 survey of the preschool nutrition program conducted in the Xiangxi Autonomous Prefecture, Hunan Province, China, we applied propensity score matching to estimate the average treatment effects on the treated children.
Results: The most striking result was that although poverty is often used as predictive of poor childhood nutrition, this effect was only significant for weight-for-age z-score and height-for-age z-score, but not for other nutritional indicators, cognition, or social emotional indexes. The results varied using different measures of poverty. The weak linkage between poverty and children's nutritional outcomes was confirmed by a series of robustness checks by changing the covariates for matching, adopting other matching methods, using bootstrapping standard errors, and building on machine learning tools.
Conclusions: A single tool of small money transfer would have limited effects, but considerable income increases that lift the poor out of poverty are important for the poor. Additionally, a mixed tool of financial support and nutritional knowledge may lead to better outcomes, especially for those living above the poverty line.

Introduction

Poverty alleviation is among the 17 Sustainable Development Goals (SDGs) of the UN 2030 Agenda for Sustainable Development. Remarkable achievements in poverty reduction have been made as the number of people worldwide living below the extreme poverty line—a daily wage <$1.90—has dramatically decreased [1,2]. China is among the largest contributors to the reduction of the number of people living in extreme poverty. In line with its tremendous economic achievement, China has made remarkable headway in alleviating poverty over the past decades [3,4]. As a key to building a moderately prosperous society, the Chinese government eliminated absolute poverty by 2020, lifting the country's 1.4 billion people out of poverty. In China, poor people are defined as those living below the official poverty line, which was set in 2011 as a per capita annual income of 2300 yuan (US $320.43) at 2010 constant prices.

Despite these achievements in poverty reduction, China continues to face increasingly serious nutrition and health issues, of which nutritional deficiencies (in poor areas) has aroused public concern. In response to these issues, the State Council issued a plan (2017–2030) to improve nutrition and health, with special programs targeting the nutrition of infants, pregnant women, students, the elderly, patients in hospital and people living in poorer regions [5]. Consequently, there has been increasing interest in the relationship between health and poverty. Most of the previous research focuses on the health of adults in general or the elderly specifically, showing that individuals with low income or education experience have worse health on average han those with higher income and better education [6,7]. However, children's health is particularly worthy of attention because health inputs in childhood play an essential role in the development of physical, mental, and emotionally mature adults. This is consistent with one of the three types of explanation for social inequalities in health as shown in Marmot et al. [8], namely *indirect selection*, suggesting that focusing on children's health is strategic for the prevention of disease and for increasing cost–benefit ratios of intervention. This

*Corresponding author. Tel: +86 (0571) 5633 6991
E-mail address: K.Chen@cgiar.org (K. Chen).

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is also confirmed by other studies showing that early life experiences may be strongly associated with children's health status in adulthood [9–12].

A rapidly growing research area investigates children's health [13–17], with a specific focus on whether this is linked to poverty. For instance, Jensen et al. [18]examine the influence of poverty on interacting biological systems underlying child development; Karpati et al. [19] found that reducing the probability of living in poverty is linked to a significant reduction in the likelihood of growth being stunted. Numerous studies have shown that although substantial progress has been, and continues to be, made in child health, indicating that rates of mortality and malnutrition among children continue to decline, concerns about large inequalities between poor and better-off children both between and within countries persist [20]. In China, little is known about the association between children's health and poverty. Specifically, far less has been done regrading whether income and parents' nutritional knowledge—as two of the most important channels shown in the next section—play a role in this association. This is an important issue for China as one of the largest developing countries to have achieved remarkable economic growth over the past 4 decades.

The present study contributes to the literature in two ways. First, it draws on a unique data set that includes individual-level child development data (e.g., biochemical indicators of nutritional status such as hemoglobin levels) while conducting interviews with principals, teachers, kitchen managers, farmers, and village leaders. The study is among the first to conduct this type of survey examining poverty and nutrition issues in rural China. The study contributes a unified set of insights about the relationship between poverty and children's nutritional outcomes, whether and how different measures of poverty are likely to change this, while suggesting key priorities to guide future policies for improving children's nutritional outcomes.

Data and methods

The present study draws on data from the September 2018 survey of a preschool nutrition program conducted in the Xiangxi Autonomous Prefecture, Hunan Province, China, supported by the World Food Program (WFP). The survey team collected data from two nationally designated counties in poverty (county Y and county L) in Xiangxi, where the rural per-capita disposable income in 2017 was comparable to the national level in 2012 [21]. The present study is focused on 26 preschools from 15 townships, of which 16 were from county Y, and 10 from county L.

The initial sample comprised several groups of people involved in the surveys with completed questionnaires, including 1334 caregivers, of whom 1319 completed the Ages and Stages Questionnaires, and 1333 completed the Strengths and Difficulties Questionnaires as the socioemotional test for the children. Participants included 28 preschool principals, 142 teachers, 26 kitchen managers, 146 smallholder farmers, and 94 village leaders. We also surveyed all children 3 or 5 y of age who attended the preschool on the survey day, with 1346 children participating in the physical examination and 1318 attending the cognitive test. Because of missing entries for some of the relevant variables, the sample was restricted to 1161 preschoolers. More detailed information is shown in the baseline report of the effects of the evaluation on the WFP preschool nutrition program [21].

The measure of poverty

There are two main measures for identifying poor households in rural China—the minimum living standard guarantee or subsistence allowance program *(dibao)*, and the national system of registering the poor (*jiandanglika*). The beneficiaries of the *dibao* program, rolled out in 2007, are mainly rural residents whose per-capita household income is lower than the local minimum standard of living. In April 2014, the State Council Leading Group Office of Poverty Alleviation and Development issued the National Poor Registration System (*jiandanglika*) to establish files and cards for households living in absolute poverty.

Here, poverty is defined based on these two measures, where the poverty indicator is 1 if the household is considered a *dibao* or *jiandanglika* program, and 0 otherwise. To further explore how the different measurements of poverty affect the main results, we also use other poverty indicators that are presented in what follows. Table 1 shows that 35% of the children live in poverty. However, there is a large body of literature that has documented that the *dibao* and *jiandanglika* programs have faced challenges in identifying poor households. For instance, Zhu and Li [22] found that only a very small overlap exists between *dibao* and low-income households. As one of the main contributions of this paper, we looked at the targeting effectiveness of the *dibao* and *jiandanglika* programs by comparing the results using the other three indicators. With the measure based on *dibao* and *jiandanglika* program as the main indicator (poverty_dj), we include the second measure (poverty_nl) based on the national poverty line in 2017 which is equal to 1 if the income per capita is <2952 Chinese yuan (US <$320.43), 0 otherwise; the third measure (poverty_il2011) is based on the international poverty line (US $1.9/d) which is equal to 2563 Chinese yuan, with Purchase Power Parity (PPP) in 2011 considered; building on the third one, the fourth measure (poverty_il2017) deducts inflation factors, yielding a corresponding poverty line of 2,850 Chinese yuan (US $397.05) in 2017.

Table 1
Summary statistics

Variable	Obs	Mean	SD	Min	Max
Poverty_dj	1161	0.35	0.48	0	1
Poverty_nl	1161	0.56	0.5	0	1
Poverty_il2011	1161	0.54	0.5	0	1
Poverty_il2017	1161	0.54	0.5	0	1
Nutritional outcomes					
WAZ	1161	−0.55	0.9	−3.57	3.64
HAZ	1161	−0.83	0.97	−4.32	5.53
WHZ	1161	−0.04	0.94	−3.93	4.33
Hb	1161	115.88	11	78	147
Stunted	1161	0.11	0.31	0	1
Wasted	1161	0.02	0.13	0	1
Underweight	1161	0.06	0.23	0	1
Overweight	1161	0.11	0.32	0	1
Obesity	1161	0.02	0.16	0	1
Anemia	1161	0.33	0.47	0	1
Cognition and socioemotional status					
VCI	1161	86.25	12.64	45	123
WMI	1161	90.64	13.36	45	129
Pemotion	1161	3.07	2.02	0	10
Pconduct	1161	1.78	1.5	0	8
Phyper	1161	4.96	2.19	0	10
Ppeer	1161	2.5	1.74	0	9
Pprosoc	1161	6.83	2.15	1	10
Pebdtot	1161	12.31	4.64	1	28

HAZ, height for age; Hb, hemoglobin; VCI, verbal comprehension index; WAZ, weight for age; WHZ, height for weight; WMI, working memory index

Table 2 provides evidence of the targeting effectiveness of the first measure. Consistent with Zhu and Li [22], it was found that some people identified as belonging to poor households are living above the poverty line, whereas others not involved in the *dibao* or *jiandanglika* program seem to be identified as poor by other measures. This suggests the need to investigate the effects on nutritional outcomes using various measures of poverty because of the inconsistency of results among these measures.

Children's nutritional outcomes

One of the most used measures of children's nutritional outcome is the height-for-age z-score (HAZ), which indicates the number of SDs a child is from the sex- and age-specific reference medians adopted by the World Health Organization [13]. For comparative purposes, children's nutritional status is also indicated by the weight-for-age z-score (WAZ). The summary statistics in Table 1 show that the mean scores of the WAZ and HAZ are −0.55 and −0.83, respectively. Together with HAZ and WAZ, we also used the weight-for-height z-score (WHZ). These key anthropometric indicators, including height and weight, are further used to calculate several proxies for child undernutrition status such as stunting, wasting, and being underweight. In line with the upward global trend of child overnutrition, we

Table 2
Comparison of targeting the poor using different measures

	Poverty_nl		Poverty_il2011		Poverty_il2017		
Poverty_dj	No	Yes	No	Yes	No	Yes	Total
No	383	366	399	350	397	352	749
Yes	126	286	134	278	133	279	412
Total	509	652	533	628	530	631	1161

also collect information about children being overweight and obese. The hemoglobin (Hb) level (shown Table 1) and the prevalence of iron deficiency anemia are included to indicate the status of micronutrient deficiency. The detailed definitions of these variables are shown in Supplementary Table 1. Anemia was the most prevalent malnutrition (33%), followed by stunting (11%). The prevalence of wasting (2%) and obesity (2%) is relatively low.

Children's cognition and socioemotional status

Based on the Chinese version of the fourth edition of the Wechsler preschool and primary scale of intelligence (WPPSI-IV), we measured the child's ability across different areas of cognition functioning and produced two index scores to show their age-based performance. Measuring the children's comprehension and reasoning, the first index—the verbal comprehension index (VCI)—is calculated using verbal skills, knowledge already gained, and how well they respond to verbal cues. Correspondingly, the second index, the working memory index (WMI), measures children's ability to memorize new information, hold it in short-term memory, concentrate, manipulate the related information to produce some results or reasoning processes, and resist interference from previously memorized items. This yields a score ranging from 70 (*extremely low*) to 130+ (*very superior*). Table 1 shows that WMI and VCI scores of sample children averaged 90.64 (average level) and 86.25 (lower than average level), respectively.

We also used the Strengths and Difficulties Questionnaire (SDQ) to capture children's mental health status in the baseline survey. The SDQ contains 25 questions testing different dimensions of children's social emotions, including emotional symptoms (Pemotion), conduct problems (Pconduct), hyperactivity/inattention (Phyper), peer relationship problems (Ppeer), and prosocial behaviors (Pprosoc). Five subset scores were obtained, of which the first four were used to calculate the total difficulties score for the children. Except for prosocial behaviors, a higher score always indicates a worse situation.

Model

As we only have one-year data, we applied propensity score matching (PSM) to estimate the average treatment effects on the treated (ATT), which represents the average effect for those children who live in poverty. H_i^T is the outcome (nutritional status) for child *i* if the child is treated (i.e., the child lives in poverty), and H_i^C is the outcome (nutritional status) for the same child if the child is untreated (i.e., the child does not live in poverty). The ATT is as follows:

$$ATT = E\left(H_i^T - H_i^C | D_i = 1\right) = E\left(H_i^T | D_i = 1\right) - -E\left(H_i^C | D_i = 1\right) \tag{1}$$

where D_i equals 1 if receiving the treatment and 0 otherwise. The underlying question is what child *i*'s nutritional outcome would be if they received the treatment, compared with not being treated. However, only one of these can be observed, whereas the other turns out to be an unknown counterfactual. Thus, we could only infer the treatment effect at the group other than the individual level under specific assumptions [23], one of which is that there are no systematical differences in unobserved characteristics between the treated and control groups that are matched on observable characteristics influencing treatment. We thus implemented PSM, using observable characteristics at the children, caregiver, and household levels to calculate the propensity score for each child.

This yielded new treatment and comparison groups that were matched based on their propensity scores until there was common support. The following conditional independence was satisfied:

$$E(X, D_i = 1) = E(X_i, D_i = 0) = E(Y_i^C | X) \tag{2}$$

The estimate ATT would be:

$$ATT = E(D = 1, PrPr (X)) - -E(D = 0, PrPr (X)) \tag{3}$$

where Pr $(D = 1|X)$ represents the probability of receiving the treatment (living in poverty) conditional on X. To investigate the effect of poverty on children's nutritional status, we matched the children living in a poor family with those living in a rich family on some individual- and household-level, socioeconomic and demographic characteristics. Supplementary Table 2 shows the descriptive statistics of these covariates including age, sex (1 = male), ethnicity (1 = non-han), family size, household average educational level (years of schooling), parental occupation (1 = high skill), and parental health (1 = healthy).

Equation [3] can be rewritten as:

$$ATT = \frac{1}{n_1} \sum_{i \in I_1 \cap S_p} \left\{ Y_{1i} - \sum_{j \in I_0 \cap S_p} W(i,j) Y_{0i} \right\} \tag{4}$$

where Y_{1i} represents child *i* in the treated group and Y_{0i} stands for child *i* in the control group, and I_1 and I_0 denote sets of children in these two groups, respectively. S_P is the region of common support. Let n_1 be the number of units in the set of $I_i \cap S_p$, and W(i, j) is the matching weights, which will be assigned to control children to form a reliable counterfactual. Depending on the choice of functional form of W(i, j), we presented the main results using nearest neighbor matching (k = 1). To ensure the robustness of the main results, rather than arbitrarily using one matching method, we adopted local linear matching, nearest neighbor matching (k = 3), and radius matching for comparative purposes. We also adopted bootstrapping SEs from 1000 iterations.

In contrast to the traditional models, the present study also examined whether the results change using generalized boosted models (GBM), a powerful machine learning method to predict a binary variable (e.g., a dichotomous treatment variable). GBM is based on an iterative fitting algorithm that starts with a single regression tree, followed by another tree at each new iteration. McCaffrey et al. [24] showed that using GBM to obtain robust propensity score weights would provide better balance properties than a simple parametric model (e.g., logistic model). This study adopts this model for the final robustness checks.

Results

Estimates of ATT

With *dibao* and *jiandanglika* as the main measures of poverty, we examined how the main results changed with other measures of poverty. Table 3 reports the estimates of ATT from PSM after matching. As stated earlier, we mainly focused on the results using the nearest neighbor matching (k = 1), which is the same as that using the regression including the poverty measure as the only variable for the matched sample. The results based on the four poverty measures are shown in columns 1, 3, 5, and 7 of Table 3, respectively.

As for Poverty_dj (based on *dibao* and *jiandanglika*) in column 1, it is found that poverty has negative effects on WAZ and HAZ. However, it is striking that those living in poverty have a higher level of Hb, which leads to a lower probability of experiencing anemia; this effect is significant at the 10% confidence level. The estimates of ATT on other indicators turn out to be statistically insignificant. This suggests that the only negative effect of poverty is on the WAZ and HAZ. More strikingly, this negative effect disappears when we use other measures of poverty, as shown in columns 3, 5, and 7.

To further minimize potential bias, we adopted bias-corrected matching estimators and show the results in columns 2, 4, 6, and 8 of Table 3 for comparative purposes. The results using adjusted estimators remained substantially unchanged.

Given the limited role of poverty in shaping child nutritional outcomes, the effects of poverty on cognition and socioemotional development are expected to be weak. Table 4 shows the estimates of the ATT. We found that there are no significant effects identified as seen from the results using poverty_dj measured by *dibao* and *jiandanglika* (col. 1). The results using bias-corrected estimators (col. 2) further confirm that there is no significant linkage between poverty and children's cognition and emotional development.

As for the other three poverty measures based on income, the children living in poverty had a lower VCI score; however, this effect disappeared when we examined the bias-corrected estimators. Regarding other cognition and emotional development indexes, there was no evidence that poverty leads to a worse situation for children, apart from VCI. This is probably because the data reveals short-term effects, whereas poverty is likely to have longer-term effects on cognition and socioemotional development. This further supports the weak link between poverty and nutritional outcomes.

Robustness checks

To ensure the robustness of the main results, we conducted a series of sensitivity analyses. The cumulative distribution before and after matching is presented in Supplementary Figure 1. Our matching strategy significantly reduced the difference between the control and treated groups. Supplementary Figure 2 shows the receiver operating characteristic curve to test the common support assumption. A value close to 0.5 would suggest a good

Table 3
Effects of poverty on children's health

	Poverty_dj		Poverty_nl		Poverty_il2011		Poverty_il2017	
	(1) Unadjusted	(2) Adjusted	(3) Unadjusted	(4) Adjusted	(5) Unadjusted	(6) Adjusted	(7) Unadjusted	(8) Adjusted
WAZ	−0.110*	−0.109*	−0.055	−0.059	−0.044	−0.053	−0.045	−0.057
	(0.064)	(0.064)	(0.057)	(0.065)	(0.055)	(0.061)	(0.056)	(0.062)
HAZ	−0.144†	−0.143†	−0.053	−0.013	−0.045	−0.015	−0.047	−0.016
	(0.067)	(0.068)	(0.061)	(0.070)	(0.060)	(0.068)	(0.060)	(0.069)
WHZ	−0.705	−1.108	1.959	−3.334	1.684	−2.671	1.693	−2.775
	(3.451)	(3.415)	(3.103)	(3.574)	(3.032)	(3.370)	(3.041)	(3.393)
Hb	1.553†	1.582†	0.440	0.216	0.563	0.512	0.691	0.633
	(0.765)	(0.766)	(0.693)	(0.814)	(0.676)	(0.763)	(0.679)	(0.769)
Stunted	0.029	0.028	0.026	0.009	0.030	0.018	0.030	0.019
	(0.022)	(0.022)	(0.019)	(0.022)	(0.019)	(0.021)	(0.019)	(0.021)
Wasted	−0.012	−0.012	0.010	0.010	0.009	0.008	0.009	0.009
	(0.010)	(0.010)	(0.009)	(0.011)	(0.009)	(0.010)	(0.009)	(0.010)
Underweight	0.019	0.020	0.012	0.010	0.009	0.007	0.009	0.007
	(0.017)	(0.017)	(0.015)	(0.017)	(0.014)	(0.016)	(0.014)	(0.016)
Overweight	−0.005	−0.003	−0.004	−0.005	0.000	−0.005	−0.000	−0.004
	(0.022)	(0.022)	(0.020)	(0.023)	(0.019)	(0.021)	(0.019)	(0.021)
Obesity	0.000	−0.000	−0.012	−0.011	−0.011	−0.014	−0.011	−0.014
	(0.010)	(0.010)	(0.010)	(0.011)	(0.009)	(0.010)	(0.010)	(0.010)
Anemia	−0.066†	−0.069†	−0.006	−0.013	−0.008	−0.017	−0.009	−0.018
	(0.033)	(0.033)	(0.030)	(0.034)	(0.029)	(0.033)	(0.029)	(0.033)
N	824	824	1018	1018	1066	1066	1060	1060

HAZ, height for age; Hb, hemoglobin; WAZ, weight for age; WHZ, height for weight
Standard errors in parentheses.
*Significant at 10%.
†Significant at 5%.

performance. In the present case, this value was 0.5, providing preliminary evidence on the robustness of the main results.

Four further robustness checks were performed. First, we removed two of the covariates used for matching, that is, father's and mother's working location, as these two variables are likely to be highly associated with parents' job type, which are also included for matching. Supplementary Table 3 shows that the balancing property is satisfied. We found that, in doing so, the results of ATT remained substantially unchanged (because of space limit, the results are not shown here).

Second, in addition to the nearest neighboring matching, we showed the results using other matching methods to see whether the main findings would change. The ATTs using local linear regression, nearest neighbor matching (k = 3), and radius matching are shown in Supplementary Tables 4 and 5. Regarding nutritional outcomes (Supplementary Table 4), the results are consistent with

Table 4
Effects of poverty on cognition and emotional development

	Poverty_dj		Poverty_nl		Poverty_il2011		Poverty_il2017	
	(1) Unadjusted	(2) Adjusted	(3) Unadjusted	(4) Adjusted	(5) Unadjusted	(6) Adjusted	(7) Unadjusted	(8) Adjusted
VCI	−0.558	−0.509	−1.690*	−0.512	−1.756*	−0.823	−1.775*	−0.796
	(0.885)	(0.888)	(0.799)	(0.953)	(0.779)	(0.884)	(0.783)	(0.890)
WMI	0.172	0.281	−1.255	−0.667	−0.916	−0.358	−0.987	−0.462
	(0.934)	(0.935)	(0.833)	(0.994)	(0.819)	(0.945)	(0.819)	(0.945)
Pemotion	0.032	0.007	0.485†	0.121	0.462†	0.152	0.453†	0.124
	(0.143)	(0.141)	(0.128)	(0.145)	(0.124)	(0.135)	(0.125)	(0.135)
Pconduct	0.015	0.011	0.126	0.181	0.062	0.060	0.068	0.072
	(0.105)	(0.105)	(0.095)	(0.110)	(0.093)	(0.102)	(0.093)	(0.103)
Phyper	−0.163	−0.152	0.214	0.379*	0.233‡	0.365*	0.228‡	0.364*
	(0.154)	(0.153)	(0.139)	(0.160)	(0.135)	(0.150)	(0.135)	(0.151)
Ppeer	−0.066	−0.074	0.061	0.026	0.032	−0.011	0.055	0.022
	(0.124)	(0.125)	(0.110)	(0.122)	(0.107)	(0.116)	(0.108)	(0.116)
Pprosoc	−0.214	−0.221	−0.194	−0.216	−0.268*	−0.292‡	−0.272*	−0.283‡
	(0.152)	(0.151)	(0.134)	(0.158)	(0.132)	(0.151)	(0.132)	(0.151)
Pebdtot	−0.182	−0.207	0.886†	0.707*	0.788†	0.566‡	0.804†	0.583‡
	(0.322)	(0.321)	(0.293)	(0.334)	(0.284)	(0.310)	(0.285)	(0.313)
	824	824	1018	1018	1066	1066	1060	106

VCI, verbal comprehension index; WMI, working memory index
Standard errors in parentheses
*Significant at 5%.
†Significant at 1%.
‡Significant at 10%.

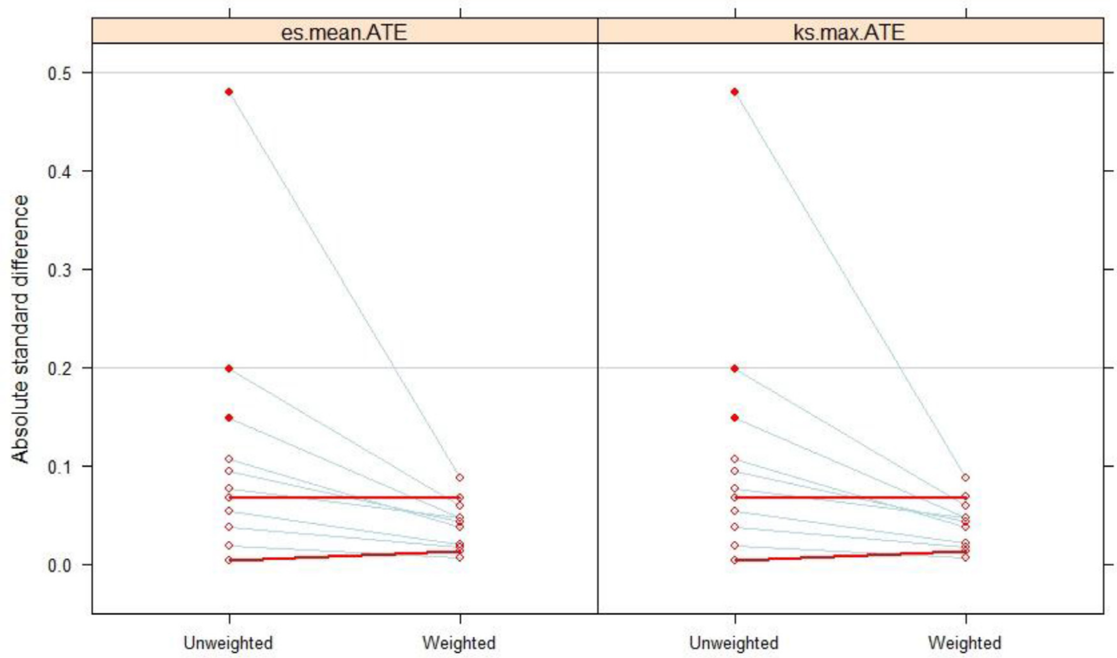

Fig. 1. Effect size plots for assessing the balance of pretreatment variables.

the findings in Table 3, indicating that WAZ and HAZ are the only two indexes that non-poverty children outperform; this effect also disappears when we change the poverty measure from *dibao and jiandanglika*-based poverty_dj to the other three income-based measures. We also found little evidence on the linkage between poverty and children's cognition and emotional development using other matching methods (Supplementary Table 5).

Third, we showed the results with bootstrapping SEs from 1000 iterations. Supplementary Table 6 indicates that although the level of significance of other indicators does not change significantly, the effect on WAZ turns to be insignificant. This further confirmed the weak linkage between poverty and children's nutritional status.

Fourth, we also adopted a machine learning method—a GBM—to estimate the robust propensity score weights and the associated ATTs. Supplementary Figure 3 shows the propensity scores for the control and treated groups. Figure 1 is used to assess the balance between groups on pretreatment variables before and after ATT weighting. The left Panel presents the results using the mean standardized bias stopping rule, and the right panel presents the results using the maximum standardized bias stopping rule. Both panels show that there is a large reduction in the differences between the means of the pretreatment variables between the unweighted and weighted samples. Building on the weights calculated by GBM, Table 5 shows the corresponding ATTs. The biggest change was that children living in poverty had much lower WHZ if we used the three income-based poverty measures. However, this was not the case when we looked at the poverty measure based on *dibao* and *jiandanglika*. Most of the other indicators were as expected. The results using this machine learning method did not provide additional evidence on the linkage between poverty and children's nutritional status.

Further discussion

The limited effects of poverty on child nutritional outcomes suggest a pivotal policy implication that only providing financial

Table 5
The results using GBM

	Poverty_dj	Poverty_nl	Poverty_il2011	Poverty_il2017
WAZ	−0.126*	−0.004	−0.007	−0.003
	(0.06)	(0.055)	(0.055)	(0.055)
HAZ	−0.165†	−0.022	−0.019	−0.021
	(0.061)	(0.058)	(0.059)	(0.058)
WHZ	0.886	−5.571‡	−5.448‡	−5.454‡
	(3.196)	(3.032)	(2.992)	(2.994)
Hb	1.753*	0.566	0.743	0.886
	(0.709)	(0.697)	(0.690)	(0.690)
Stunted	0.024	0.021	0.022	0.021
	(0.021)	(0.019)	(0.019)	(0.019)
Wasted	−0.006	0.001	0.002	0.002
	(0.009)	(0.009)	(0.008)	(0.008)
Underweight	0.024	0.009	0.010	0.010
	(0.015)	(0.014)	(0.014)	(0.014)
Overweight	0.001	0.001	0.008	0.007
	(0.021)	(0.020)	(0.019)	(0.019)
Obesity	−0.004	−0.007	−0.007	−0.007
	(0.011)	(0.010)	(0.010)	(0.010)
Anemia	−0.066*	−0.019	−0.023	−0.028
	(0.029)	(0.029)	(0.029)	(0.029)
VCI	−0.210	−0.659	−0.666	−0.759*
	(0.818)	(0.776)	(0.776)	(0.775)
WMI	−0.263	−0.132	0.355	0.374
	(0.883)	(0.832)	(0.825)	(0.824)
Pemotion	0.088	0.158	0.178	0.191
	(0.130)	(0.121)	(0.120)	(0.121)
Pconduct	0.040	0.068	0.053	0.054
	(0.099)	(0.090)	(0.090)	(0.090)
Phyper	−0.100	0.231*	0.218	0.215
	(0.144)	(0.134)	(0.133)	(0.133)
Ppeer	−0.080	0.050	−0.009	−0.000
	(0.111)	(0.104)	(0.103)	(0.103)
Pprosoc	−0.227	−0.179	−0.188	−0.201
	(0.141)	(0.136)	(0.133)	(0.133)
Pebdtot	−0.053	0.507‡	0.439	0.460
	(0.306)	(0.282)	(0.282)	(0.282)

HAZ, height for age; Hb, hemoglobin; VCI, verbal comprehension index; WAZ, weight for age; WHZ, height for weight; WMI, working memory index
Standard errors in parentheses
*Significant at 5%.
†Significant at 1%.
‡Significant at 10%.

Table 6
Income simulation

	Original sample		Counterfactual		
Variables	N	Mean	N	Mean	Mean Diff
WAZ	1161	−0.55	1397	−0.50	−0.04
HAZ	1161	−0.83	1397	−0.77	−0.06
WHZ	1161	45.81	1397	45.43	0.38
Hb	1161	115.88	1397	115.37	0.50
Stunted	1161	0.11	1397	0.10	0.01
Wasted	1161	0.02	1397	0.02	−0.00
Underweight	1161	0.06	1397	0.05	0.01
Overweight	1161	0.11	1397	0.11	−0.00
Obesity	1161	0.03	1397	0.03	−0.00
Anemia	1161	0.33	1397	0.35	−0.02
VCI	1161	86.25	1397	86.54	−0.28
WMI	1161	90.64	1397	90.82	−0.17
Pemotion	1161	3.07	1397	3.04	0.03
Pconduct	1161	1.78	1397	1.77	0.01
Phyper	1161	4.96	1397	5.00	−0.04
Ppeer	1161	2.50	1397	2.51	−0.01
Pprosoc	1161	6.83	1397	6.92	−0.09
Pebdtot	1161	12.31	1397	12.32	−0.01

HAZ, height for age; Hb, hemoglobin; VCI, verbal comprehension index; WAZ, weight for age; WHZ, height for weight; WMI, working memory index

support for poor households may not lead to significant improvements in the nutritional status of poor children. In this case, we are interested in what matters in intervention programs that aim to improve child nutritional outcomes. We first examined whether an increase in income would affect nutritional outcomes using a simple simulation, which reveals how the nutritional outcomes would change if the poor were lifted out of poverty.

This simulation yielded a counterfactual sample in which all the poor children were correspondingly matched with better-off children based on the matching method. Comparing the nutritional outcomes of this counterfactual sample with the original sample raises understanding of whether income increases will result in an improvement in the nutritional indicators. The results in Table 6 show that there are no significant differences in most of the indicators, which suggests that the role of financial support aimed at improving poor children's nutritional outcomes would be limited.

Given the limited role of income, the key challenge was understanding what really matters. A potential factor is the nutrition knowledge of caregivers that may affect children's dietary diversity and food consumption. To examine how poverty affects a household's investment in children's food and nutrition, we included selected food consumption variables related to questions asked about the expenditures in the previous month on food (in total), sweetmeats, fruit, protein (meat, eggs, and milk), nutrient, and iron supplements. Following Bi et al. [20], we also used the dietary diversity score (DDS) to measure the food diversity of children over the previous 24 h, across nine diverse food groups.

Under the guidelines of the Food and Agriculture Organization (FAO) of the United Nations, the score was calculated by counting the number of food groups consumed in the past 24 h without consideration of a minimum quantity requirement for any food group. We also calculated a nutrition awareness score based on 11 questions regarding caregivers' knowledge about children's feeding practices and nutrition. For each of the questions, a correct response scored 1 point; in the case where there was more than one correct choice, all the correct choices shared 1 point, resulting in a score ranging between 0 and 11.

To investigate the association between poverty and parental nutrition knowledge, we used the PSM method to obtain the estimates of ATT, with the results shown in Table 7. It was found that poverty had negative effects on the nutrition knowledge of caregivers, which are significant using all the matching methods. Although the results using other measures of poverty do not always show significant associations, most of the estimates are negative. This suggests that the caregivers of the children from poor households are likely to have worse nutrition knowledge than those from better-off households, which may further lead to less expenditure on some of the main food items.

Thus, we explored how poverty affects children's dietary diversity and food consumption. Table 8 shows the estimates of the ATT using nearest neighbor matching. The first row shows that the poor children are likely to have lower DDSs in the case of all three income-based poverty measures. The effect of poverty on food consumption in the previous month for the child is shown to be negative and significant at the 5% significance level. More specifically, the negative effect of poverty on expenditures on fruit are significant using all the poverty measures, whereas fewer expenditures on meat, nutrition supplements, and iron are also identified using some of the poverty measures.

These results suggest that, to improve child nutritional outcomes, merely providing money would not work; improving nutrition knowledge would help caregivers invest more in the food for their children. However, a remaining question is whether this differs between the extreme poor and better-off individuals. To further examine this issue, we partitioned the sample into the poor and those living above the poverty line as stated earlier, and conducted a series of regression analysis, as shown in Table 9. In columns 1 and 2, we regress caregivers' nutrition knowledge on the logarithm of household income per capita for the two groups separately. It was found that the coefficient was positive and significant for the non-poor but insignificant for the poor. This result persisted when the dependent variable is DSS in columns 3 and 4. This suggested that the income effect was limited within the poor. The income effect would be large if the financial support was large enough to lift the poor out of poverty. In columns 5 and 6, we further showed that the association between caregiver nutrition knowledge and children's DDS, finding that that caregiver nutrition knowledge plays a larger role for the non-poor.

Table 7
Effects of poverty on parental nutrition knowledge

	Poverty_dj	Poverty_nl	Poverty_il2011	Poverty_il2017
Nearest (k=1)	−2.99*	−5.09*	−5.14*	−5.02*
Local linear matching	−2.72†	−1.21	−1.35	−1.30
Nearest (k=3)	−2.57†	−1.10	−1.18	−1.51
Radius matching	−3.01*	−0.24	−1.70	−1.71

Standard errors in parentheses
*Significant at 1%.
†Significant at 5%.

Table 8
Effects of poverty on food consumption

	Poverty_dj		Poverty_nl		Poverty_il2011		Poverty_il2017	
	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted
DDS	−0.010	0.005	−0.281*	−0.154†	−0.287*	−0.163‡	−0.285*	−0.159†
	(0.085)	(0.084)	(0.075)	(0.087)	(0.073)	(0.082)	(0.073)	(0.083)
Food	−64.919*	−62.508*	−113.679*	−68.999‡	−111.877*	−78.962*	−111.950*	−77.022*
	(24.285)	(24.100)	(25.971)	(26.955)	(24.979)	(25.217)	(25.107)	(25.379)
Candy	−15.807‡	−15.865‡	−24.058*	−11.131	−23.667*	−14.355†	−23.897*	−14.504†
	(7.508)	(7.430)	(7.953)	(7.814)	(7.654)	(7.358)	(7.690)	(7.414)
Fruit	−18.084†	−17.791†	−42.607*	−28.134*	−39.687*	−27.016*	−40.178*	−27.142*
	(10.171)	(9.853)	(8.779)	(9.212)	(8.593)	(9.102)	(8.624)	(9.123)
Meat	−34.813*	−33.939*	−37.935*	−21.008	−37.228*	−24.047†	−37.342*	−23.368†
	(12.682)	(12.407)	(11.958)	(13.331)	(11.591)	(12.487)	(11.654)	(12.595)
Sup	11.138	11.000	−33.685*	−28.693‡	−30.135*	−24.983‡	−32.197*	−28.035‡
	(10.845)	(11.071)	(10.349)	(11.974)	(10.084)	(11.210)	(9.971)	(10.876)
Iron	3.496	3.503	−6.775‡	−7.103‡	−7.061‡	−7.474‡	−7.101‡	−7.499‡
	(3.581)	(3.614)	(3.302)	(3.562)	(3.157)	(3.194)	(3.175)	(3.231)

DDS, dietary diversity score; Sup, supplement
Standard errors in parentheses
*Significant at 1%.
†Significant at 10%.
‡Significant at 5%.

Table 9
Heterogeneous effects between the poor and non-poor

	Nutrition knowledge		DDS		DDS	
	Poor	Non-poor	Poor	Non-poor	Poor	Non-poor
Log (income)	0.457	2.369*	−0.048	0.087†		
	(0.81)	(0.45)	(0.07)	(0.04)		
Knowledge					0.008‡	0.012*
					(0.00)	(0.00)
Constant	22.826*	11.275*	6.166*	5.184*	5.555*	5.464*
	(6.25)	(3.76)	(0.54)	(0.34)	(0.12)	(0.10)
N	258	572	258	572	412	749
F	0.318	27.546	0.480	4.645	3.495	14.205

N denotes the number of observations and F denotes the F-statistics. DDS, dietary diversity score
Standard errors in parentheses
*Significant at 1%.
†Significant at 5%.
‡Significant at 10%.

Combing these results, we further concluded that a single tool of small money transfer would have limited effects, but considerable income increases that lift the poor out of poverty are important for the poor. Additionally, a mixed tool of financial support and nutrition knowledge improvement may lead to better outcomes, especially for those living above the poverty line.

Conclusion

This study added to the growing literature that seeks to examine the relationship between poverty and child nutritional outcomes using a unique data set from the poor South-Central region of China. The study's results lead to several findings and suggest some policy implications for other countries. First, the link between poverty and nutritional outcomes is weak. This suggests that poverty reduction programs in developing countries should pay more attention to how these programs would lead to better nutritional outcomes for the poor. Second, using different measures of poverty yields different results that challenges our first conclusion. This suggests that the *dibao* and *jiandanglika* programs in China did not effectively target the poor, and that policies aiming to improve the nutritional outcomes of poor children require additional effort to identify the poor using different measures. As for other countries, the implication is that multidimensional indexes of poverty are preferred in policy evaluations. Third, income increase as a single policy tool has limited effects on the improvement in child nutritional outcomes. A further investigation indicates that the inadequate nutrition knowledge of caregivers is one of the challenges facing the poor in improving child nutritional outcomes as poor caregivers have limited knowledge about food diversity and spend less on the food of children. This suggests that, as for the financial support programs aiming to improve children's nutritional outcomes in developing countries, the amount of money transferred should be large enough to lift the poor out of poverty; otherwise, a mixed tool of financial support and nutrition knowledge improvement would be more useful. As for the non-poor, the important role of nutrition knowledge is highlighted because increased income is likely to be spent unwisely due to the lack of nutrition knowledge of caregivers.

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Supplementary materials

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