



Inequality of opportunity in children's nutritional outcomes in China

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ABSTRACT

Using pooled data from the 1991–2011 waves of the China Health and Nutrition Survey (CHNS), this paper proposes an empirical study on inequality of opportunity in child nutritional outcomes. Children's nutritional outcomes were measured using anthropometric indicators including underweight, stunting, wasting, overweight and obesity. We examine the role played by circumstances beyond the control of individuals—for instance, children's age, gender, hukou status, household size, birth order, family background, region and sanitation—in generating nutritional outcomes inequality among Chinese children aged 0–15. We find that the largest relative share of inequality of opportunity (IOP) in child nutritional outcomes in China is 11.49% (stunting) for the entire sample. Shapley-value decompositions reveal that region and family background are the dominant contributors to inequality of opportunity for most of the nutritional outcomes. IOP turns out to be largest for the 6–10 age cohort. Heterogeneity analysis further shows that disadvantaged groups, for instance, children living in the rural area of western China, face higher unequal opportunities for undernutrition. Conversely, children from urban area of the east show a higher inequality of opportunity in overnutrition. In addition, our counterfactual analysis indicates that if those rural children had migrated to cities, the IOP for the full sample would increase by more than 19%, implying greater attention should be paid to equalizing opportunity amid massive migration and urbanization in China in the years to come.

1. Introduction

A growing body of literature suggests that the well-documented socioeconomic status (SES) related health inequalities originate from childhood or even prenatal period (Case et al., 2002; Currie 2011). Childhood health inequality can be translated into inequality in other domains in adulthood (Almond et al., 2018) and further be transmitted to the next generation, causing the intergenerational transmission of poverty and inequality (Walker et al., 2011). As a predictor and indicator of child poor health status (Black et al., 2003), child malnutrition is suggested to be strongly linked with poor health outcomes such as childhood mobility and mortality, poor cognitive and non-cognitive skills and labor market outcome in adult life (Alderman et al., 2006). 149.2 million children under 5 suffered from stunting, and 38.9 million children under 5 were overweight globally in 2020 (UNICEF, 2021). This was exacerbated by deteriorations in household wealth and disruptions to the availability and affordability of nutritious food and essential nutrition services caused by COVID-19, with the poor being

affected disproportionately. Motivated by these findings, there is growing consensus on addressing issue of poverty and inequality from a lifecycle perspective via placing more emphasis on tackling childhood malnutrition.

Two aspects of literature on child health inequality are relevant to the present study. First is research investigating the socioeconomic determinants of child health and/or nutrition inequality. For example, many studies investigate the role of socioeconomic status (Case et al., 2002), parental education (Chen et al., 2021), parental migrant status (Chen et al., 2014; Zhang et al., 2021), region (Ervin and Bubak, 2019; Van de Poel et al., 2007), and income- or wealth-related inequality in child health (Aristides dos Santos et al., 2019; Srinivasan et al., 2013). Second is the strand of studies calculating the level of child health inequality index using Gini coefficient or concentration index (Doorslaer and Koolman, 2004) and a range of decomposing methods, including Blinder-Oaxaca decomposition analysis (Sharaf and Rashad, 2016), unconditional quantile regressions and counterfactual decomposition (Ghosh et al., 2020).

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The aforementioned studies, however, did not attempt to distinguish between legitimate and illegitimate part of child nutrition inequality. It is the illegitimate part of the inequalities—referred to as inequality of opportunity (IOP)—that is ethically objectionable and thus should be fixed (Alesina and Angeletos, 2005). The framework of equality of opportunity was first introduced into economics by Roemer (1998). Based on this notion, overall inequality can be divided into two parts: inequality caused by factors beyond and within the individual's control, called circumstances and effort, respectively. This framework is used in explaining inequality of opportunity in a wide range of outcomes, including income (Ferreira and Gignoux, 2011; Golley et al., 2019; Yang et al., 2021), adult health (Davillas and Jones, 2020; Ding et al., 2021), education (Golley and Kong, 2018) and consumption (Singh, 2012; Shi, 2019).

China offers an interesting and unique case for studying IOP in nutrition among children. First, China's income inequality and health inequality has been increasing over the last four decades, particularly in terms of rural-urban disparities. Existing evidence suggests that although children's average health status has improved in China, the rural-urban gap remains (Liu et al., 2013) and the inequality on child health status has even widened (Chen et al., 2014). Second, China is undergoing the world's largest internal migration, resulting in a high proportion of rural children left behind by at least one of their parents (Zhang et al., 2015). It is, therefore, important to investigate how and to what extent the role that children's migration status play in explaining their nutrition inequalities.

This study contributes to the literature in several important ways. First, to the best of our knowledge, this is the first attempt to apply the IOP framework to children's malnutrition status in the context of China. Second, we pay special attention to the rural-urban differentials of IOP in children's nutritional outcomes by conducting a subsample heterogeneity analysis. Moreover, a counterfactual analysis was conducted to explore the impacts of migration on the nutritional status of left-behind children. Third, since our data cover the years from 1991 to 2011 during which the massive internal migration occurred, this allows us to sketch the changes over time, enabling better understanding of the trend and patterns of inequality of opportunity during the study period.

2. Methods

Our study follows the idea of measuring inequality of opportunity in income stemming from Roemer (1998) which partitions factors that affect individual outcomes (e.g. income) into effort and circumstances. Overall, our methodology can be summarized into two steps. First, in the case of IOP in health, we begin with a finite population of individuals, $i \in \{1, \dots, N\}$, corresponding to the health distribution of this population $\{y_i\}$ where y_i is a function of a vector of effort, E_i and a vector of circumstances, C_i . The population can be divided into J "types", given $\Pi \{T_1, \dots, T_j\}$, in which individuals have identical circumstances: $C_h = C_l$, $\forall h, l/h \in T_j, l \in T_j$. The maximum number of types is $J = \prod_{v=1}^V x_v$, where x_v refers to the number of values each of the circumstances take on. Based on this definition, we adopt parametric estimation methods to calculate the overall IOP (refer to Step 1 in Appendix 1 for details). Second, we use a Shapley-value decomposition to measure the extent to which each circumstance contributes to overall inequality of opportunity. The main idea is that inequality decompositions relate to the order in which inequality from a particular circumstance is included. This suggests that the contribution of each circumstance is calculated by the average change in inequality over all possible inclusion sequences (refer to Step 2 in Appendix 1 for details).

3. Data, variables and summary statistics

3.1. Data

The data used were drawn from the China Health and Nutrition Survey (CHNS), an ongoing international collaborative project between the Carolina Population Center at the University of North Carolina and the Chinese Center for Disease Control and Prevention. The CHNS covers 15 provinces and municipalities that vary substantially in geography and levels of economic development. The sample were drawn using a multistage, random cluster process covering approximately 7200 households with over 30,000 individuals for the years 1989, 1991, 1993, 1997, 2000, 2004, 2006, 2009, 2011 and 2015. One key advantage of CHNS is that body height and weight were measured by trained nurses rather than being self-reported. In addition, CHNS is one of the most comprehensive health surveys covering the longest time span in China (Deschenes et al., 2020).

The following analysis uses seven waves of CHNS, namely CHNS1991, 1993, 2000, 2004, 2006, 2009, 2011. We did not include CHNS1989, 1997, 2015 because of many missing values for information on children's height and weight and circumstance variables. We restricted our sample to children aged 0–15. After excluding those outside the 0–15 age range and those with missing entries for some of the relevant circumstances variables, the final study sample is a pooled sample with 11,387 observations.

3.2. Nutritional outcomes

Anthropometric measures were used to indicate children's nutritional status. First, based on children's height and weight, we calculated four continuous variables, namely height for age Z-score (HAZ), weight for age Z-score (WAZ), weight for height Z-core (WHZ) and BMI for age Z-score (BMIZ). Details for generating these scores could be found from World Health Organization (2006). Based on these continuous variables, five dummy variables were constructed accordingly, including under-nutrition indicators—underweight, stunting, wasting, and overnutrition indicators—overweight and obesity.

3.3. Circumstance factors

This paper used nine types of circumstances variables including age, gender, hukou status, household size, birth order, region, family background, sanitation, and year dummies, all of which are beyond the control of individual child.

Age and gender differences in child development have been investigated by extant studies (Chen et al., 2021; Weber et al., 2017). With respect to gender, existing studies suggest the gender differentials in parents' human capital investment, but the results are mixed and context-specific (Francesconi and Heckman, 2016). This may, to some extent, indicate that cultural factors may play a role when parents make such decisions. For example, in some Asian countries such as China and India, sons are generally preferred than girls due to the traditional so called "son preference"; therefore, sons may be at an advantage in intra-household resources allocation (Asadullah et al., 2021; Rahman, 2019).

The third circumstance variable is hukou status. Numerous studies have documented the rural-urban disparity in children's health (e.g., Van de Poel et al., 2007; Ervin and Bubak, 2019). This is likely to be more pronounced in China where a residence registration system (called the hukou system) was enforced to restrict internal migration and an individual is only entitled to enjoy certain welfare such as medical insurance in his/her hukou area (Zhang et al., 2021).

Child health status may be linked with the number of household members and child birth order, as indicated by literature on the tradeoff between child quantity and quality within a family (Black et al., 2005; Hatton et al., 2018). That said, we add both household size and birth

order as circumstance factors.

To take into account of vast regional variation across China, we include region (categorized into east, middle and west) as another circumstance variable. The ideal circumstance for obtaining the effect of region would have been the region of birth. However, due to absence of such information, we follow Singh (2012) to use geographical region of residence as a proxy for region of birth.

We use family background proxied by father’s educational attainment and occupation as well as mother’s educational attainment and occupation. This is motivated by empirical evidence on the association between parental background and children’s development (Behrman and Rosenzweig, 2002; Currie and Moretti, 2003). The main mechanisms may include that parents from higher background are better at utilizing health care facilities and processing information.

Sanitation, including access to clean tap water and having a flushing toilet in the house is shown to be positively linked with children’s health (Ngure et al., 2014). As a measurement of household sanitary condition levels, we create its index from the following two dummy variables: (i) access to drinking water, and (ii) having in-house flushing toilet.

Lastly, we include year dummies in pooled cross-sectional regressions to capture time-varying macroeconomic factors that may affect child nutritional outcomes.

3.4. Summary statistics

Table 1 reports summary statistics for key outcome variables and circumstance variables used in this study. The highest prevalence of malnutrition in our sample is obesity followed by stunting and overweight. The incidence rates for wasting and underweight are both 5%. In terms of circumstance factors, the average age for our sample children is 8.79. 53% of sample children are boys, and about one third of them have urban hukou. They are from households with an average of 4.52

Table 1
Summary statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
Outcome variables					
Stunting	11,387	0.10	-	0	1
Wasting	11,387	0.05	-	0	1
Underweight	6,903	0.05	-	0	1
Overweight	11,387	0.08	-	0	1
Obesity	11,387	0.11	-	0	1
Circumstances					
Age	11,387	8.79	4.02	0	15
Gender					
Male (=1)	11,387	0.53	-	0	1
Hukou					
Urban (=1)	8,496	0.33	-	0	1
Household size	11,386	4.52	1.31	3	13
Birth order	11,387	1.73	0.87	1	7
Region					
East	11,387	0.31	-	0	1
Middle	11,387	0.40	-	0	1
West	11,387	0.29	-	0	1
Mother’s education					
Middle school and above (=1)	11,354	0.55	-	0	1
Father’s education					
Middle school and above (=1)	11,345	0.70	-	0	1
Mother’s occupation					
Off-farm employment (=1)	9,778	0.49	-	0	1
Father’s occupation					
Off-farm employment (=1)	10,714	0.52	-	0	1
Toilet					
In-house flushing toilet (=1)	11,367	0.29	-	0	1
Water					
Tap drinking water (=1)	11,363	0.64	-	0	1

Notes: The smaller sample size for underweight is because this measure only applies for children aged between 0 and 10 according to WHO child growth standards (WHO, 2006). There are 6903 children aged equal or under 10 in our sample.

household members. The average child birth order is 1.73. Proportions of them from east, middle and west part of China are 31%, 40% and 29%, respectively. The proportion for having an educational attainment higher than middle school is 55% for mothers and 70% for fathers. Fathers are more likely to engage in off-farm employment than mothers, with the probability being 52% and 49%, respectively. Moreover, 29% of our sample households have in-house flushing toilet and 64% of them have access to tap drinking water.

4. Results

4.1. IOP in children’s nutritional outcomes

Panel A of Table 2 shows the overall inequality of opportunity based on the regressions of nutritional outcomes on circumstances. Since the dependent variables are all binary, these regressions were estimated using probit model. The results show that the magnitude of IOP in stunting is the largest, indicating that 11.49% of the inequality of the prevalence of stunting stems from the observed circumstances. In contrast, the contribution of the observed circumstances is the lowest (about 3.64%) for the prevalence of wasting. The magnitudes of IOP in the other three binary measures namely underweight, overweight and obesity ranges from 6.90% (overweight) to 9.13% (obesity).

Panel B of Table 2 reports the contribution of each of the circumstances to the IOP using the Shapley decomposition method.¹ Geographical region accounts for the largest part of the IOP in all the five nutritional outcomes, ranging from 22% for stunting to 32% for wasting and overweight. Family background (in combination) remains the second dominant contribution in three of the five outcomes (except wasting and obesity). While age and gender have been taken into account to construct the five nutritional outcomes, it is not surprising that the contribution of these two circumstances is not that large. For instance,

Table 2
Inequality of opportunity in child nutritional outcomes (pooled sample).

	Stunting	Wasting	Underweight	Overweight	Obesity
Panel A. Overall inequality of opportunity (%)					
IOP	11.49	3.64	7.92	6.90	9.13
Panel B. Decomposition (% of IOP)					
Age	1.75	26.69	9.54	6.36	14.31
Gender	0.07	1.69	0.88	3.51	7.22
Hukou	11.25	7.03	8.33	11.80	5.27
Household size	4.87	3.25	3.94	7.13	0.55
Birth order	4.19	7.22	3.34	5.72	1.32
Region	22.09	32.23	24.24	32.49	23.03
Family background	26.75	9.49	25.99	13.98	8.03
Sanitation	11.25	3.59	12.15	9.44	3.02
Year effect	17.68	8.83	11.53	9.56	37.26
N	6761	6761	4000	6761	6761

Notes: IOP refers to the overall inequality of opportunity; family background includes both fathers’ and mothers’ education and occupation; sanitation includes access to in-house toilets and tap water. The sample sizes in this table and the tables in what follows are different for different outcomes depending on data availability. Note that some variables have many missing values especially hukou and mother’s occupation variables. This means that the number of observations in each regression are different from those reported in summary statistics. Sample size for underweight is smaller for the same reason as stated in the notes of Table 1.

¹ Factors such as health care quality and food access are also potential important determinants of child nutritional outcomes. Their impact are absorbed in other circumstance variables such as gender, family background and geographic region. Since health care quality and food access are not widely adopted as circumstances in the literature on IOP, examining their role is beyond the scope of this study and remains fruitful avenues for future research.

the contribution of gender to the IOP in stunting is as low as 0.07%. However, the contribution of age to the IOP in wasting and obesity are higher than expected, valuing at 27% and 14%, respectively. Noticeably, hukou's contribution to IOP is larger than 10% in stunting and overweight. Sanitation also plays an important role in nutrition inequality, especially in the case of stunting and underweight, for which the partial contributions are 11% and 12%, respectively. It is worth noting that year dummies are the single most important factor in explaining IOP in child obesity. In contrast, the contributions of birth order and household size are relatively marginal across the nutritional indicators.

We also conducted sensitivity analysis to test the robustness of our main findings. First, we use WAZ, HAZ, WHZ and BMIZ as alternative outcome variables. Equation (3) would be estimated using OLS and MLD index rather than modified dissimilarity index in this case. Table 3 presents the results of IOP using these four measurements. Panel A shows that the overall IOP ranges from 3.48% to 12.82%, which is practically comparable to the IOP in Table 2 which ranges from 3.64% to 11.49%. Panel B shows the contribution of each observed circumstances to the overall IOP. Consistent with the results presented in Table 2, we find that region, family background and year effects are the largest contributors in most cases. These results may provide us more confidence not only in terms of the measurements of inequality, but also of the choice of nutritional outcomes.

The IOP literature has suggested that, due to data limitations, the observed circumstances included in the estimation of IOP are only a subset of all the circumstances that affect the outcomes. This suggests that the estimated $\hat{\beta}$ in Equation (4) could be biased and cannot be considered as causal relationship between the circumstances and the outcomes. We thus interpret the results with caution and follow Ferreira and Gignoux (2011) to argue that it is not important for the overall measure of IOP which could be considered as lower-bound estimates of the "real" IOP. Bearing this in mind, we also intend to examine how IOP would change if there were more circumstances included. In Table 4, we re-estimate IOP by adding two more circumstances including fathers' and mothers' nutrition knowledge and find that IOP in the five binary outcomes ranges from 4.26% to 10.72%. Among these outcomes, the results with respect to wasting and underweight are practically identical. This suggests that the choice of circumstances in this study are reasonable as indicated by previous literature.

4.2. IOP heterogeneity: time, age and region dimensions

We estimate the IOP for each year and present the results in Table A4 in Appendix 4. To have a clear look at the trend over years, we further plot the results in Panel A of Fig. 1. Our results indicate that the magnitude of IOP ranges from 4% (for wasting in 1993) to 16% (for obesity in 2006). All the IOPs present an increasing trend before 2011 with the only exception for stunting which decreased over the sample period. We further divided the five nutritional outcomes into two categories including undernutrition (underweight, stunting and wasting)

Table 3
Inequality of opportunity in alternative nutrition measurements.

	WAZ	HAZ	BMIZ	WHZ
Panel A. Overall inequality of opportunity (%)				
IOP	5.82	12.82	6.03	3.48
Panel B. Decomposition (% of IOP)				
Age	5.65	51.68	31.95	5.60
Gender	1.16	0.95	3.89	0.97
Hukou	7.49	4.02	3.69	1.06
Household size	0.88	0.57	4.00	19.01
Birth order	4.67	0.47	2.03	3.30
Region	34.88	13.91	20.89	17.27
Family background	11.30	11.65	7.05	23.64
Sanitation	5.46	2.34	2.89	5.76
Year effect	28.47	14.33	23.61	23.40
N	1744	2687	2627	762

Table 4
Re-estimating inequality of opportunity including nutritional knowledge.

	Stunting	Wasting	Underweight	Overweight	Obesity
Panel A. Overall inequality of opportunity (%)					
IOP	9.14	4.26	6.63	8.61	10.72
Panel B. Decomposition (% of IOP)					
Age	0.53	5.17	7.50	9.29	11.06
Gender	1.32	3.57	0.47	0.31	12.49
Hukou	9.35	9.36	7.54	11.30	7.02
Household size	2.96	1.56	2.55	7.46	0.68
Birth order	5.69	2.40	2.79	9.22	2.65
Region	26.25	21.72	29.03	27.11	45.22
Family background	25.60	25.05	28.88	21.18	10.78
Sanitation	11.33	3.53	10.25	6.26	1.80
Nutrition knowledge	5.34	15.54	4.85	5.17	1.96
Year effect	11.63	12.10	6.01	2.66	6.34
N	3051	3051	1838	3051	3051

and overnutrition (overweight and obesity). As shown in Panel B, both IOPs in undernutrition and overnutrition peak at 2009 followed by a decrease in 2011 despite a much sharper decrease in undernutrition.

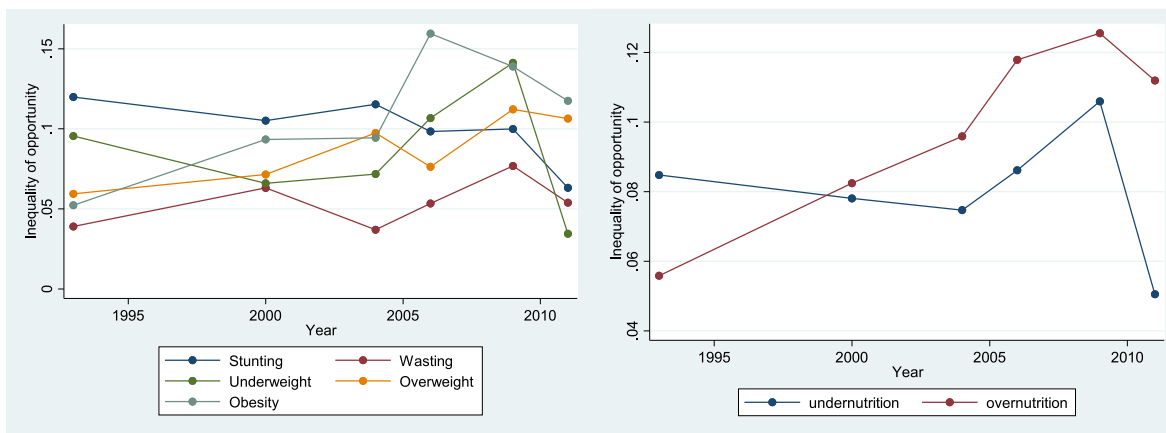
In addition to the trend over years, we are also interested in looking at whether and how IOP changes across age cohorts. The full results for the three cohorts are shown in Table A5 in Appendix 5 while the simplified main results of IOP are plotted in Panel A of Fig. 2. IOP is generally higher for stunting (peaking at 13.5% for the oldest group) than for other outcomes. In addition, IOP in stunting shows an opposite trend across age cohorts compared to obesity, with the former presenting the highest value for the oldest group and lowest value for the youngest group, and the latter presenting the highest value for the youngest group and the lowest value for the oldest group. As for all other three outcomes, the IOP peaks at the middle age group. We further averaged the IOPs into undernutrition and overnutrition for each age cohort in Panel B of Fig. 2. We find that those aged 6–10 years old have the highest IOPs for both undernutrition and overnutrition.

Next, we partition the population into three region groups—including east, middle and west to explore the differentials in the IOP across regions. Panel A of Fig. 3 shows that the largest IOP in the single nutritional outcome is as high as 16.7% in the case of stunting in the west region. Panel B reveals that IOP in undernutrition is the largest in west China while that in overnutrition is the largest in east China. These results may suggest that regions with worse economic conditions (e.g. the west of China) are likely to be associated with more unequal opportunities for enhancing children's undernutrition. In contrast, children from better-off regions are facing greater challenges of overcoming inequality of opportunity in overnutrition. The full results with details in decomposition are shown in Table A6 in Appendix 6.

4.3. A further look into the rural-urban disparities

Although the results in Table 2 shows that hukou is not the dominant circumstance, the contribution of hukou to the IOP is considerable. Thus, it is worth investigating how the IOPs differ between those with rural and those with urban hukou. Panel A of Fig. 4 shows that the IOP in stunting for those with rural hukou is the most substantial (12.1%), much higher than their counterparts entitled with urban hukou (4.7%). The IOPs in wasting and underweight for those with rural hukou also outnumber those with urban hukou. Despite the larger IOPs in overweight and obesity for those with urban hukou, Panel B shows that the average IOP in nutritional outcomes for urban children (6.7%) are lower than that for rural children (7.6%).

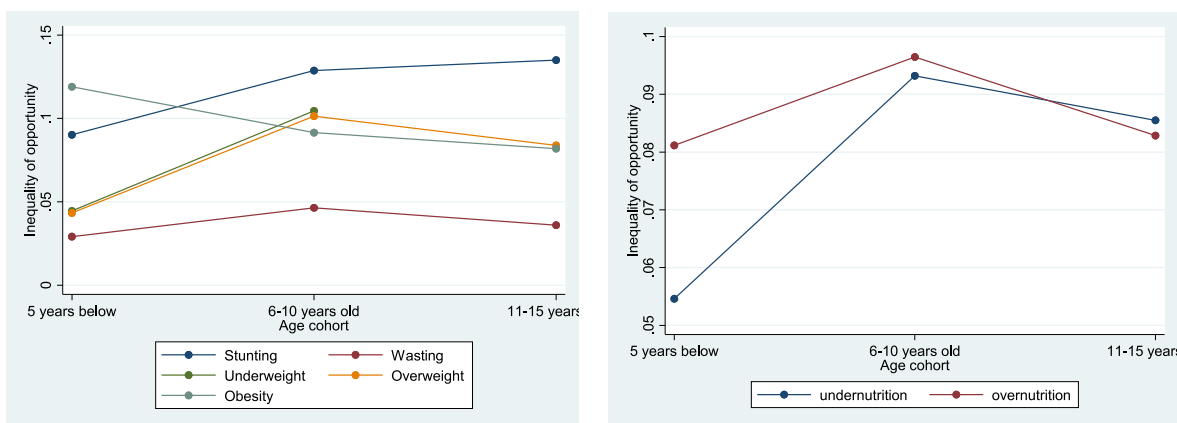
Previous studies suggest that nutrition intake is one of the most pivotal factors driving the rural-urban health disparities in China (Chang et al., 1994). To test this, we further examine the different opportunities in macronutrient intakes for these two subsamples separately. As we



Panel A

Panel B

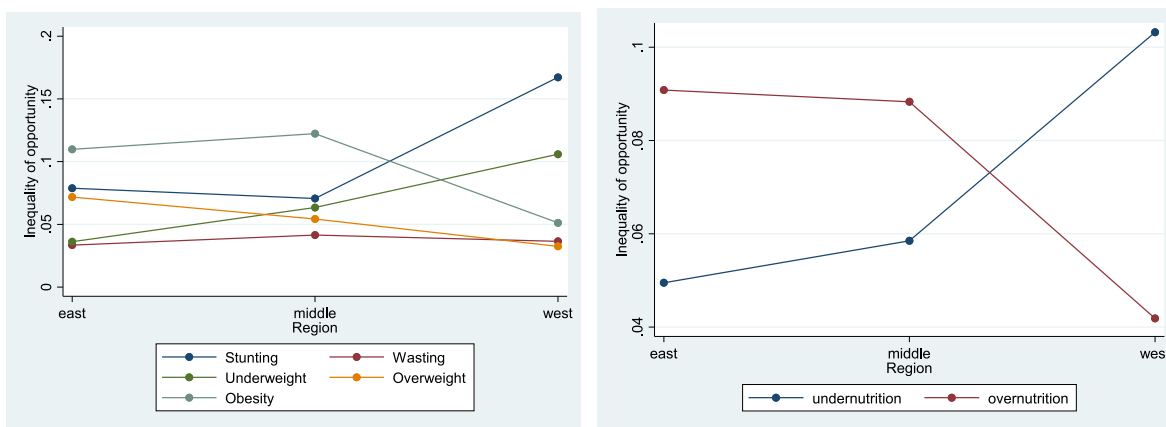
Fig. 1. Trend of inequality of opportunity in children's nutritional outcomes.



Panel A

Panel B

Fig. 2. Inequality of opportunity in children's nutritional outcomes across age cohorts.



Panel A

Panel B

Fig. 3. Inequality of opportunity in children's nutritional outcomes across regions.

have the data for the 3-day average intakes of carbohydrate, fat and protein, we recode them into dummies which equal to 1 if relative macronutrient intakes are within the acceptable macronutrient distribution range (AMDR) and equal 0 otherwise (see Appendix 2 for a detailed description of this procedure). AMDR is a healthy range of

intake of a particular energy source such as carbohydrate, fat and protein. Intakes outside this range is linked with an increased risk of chronic disease and fail to meet the requirement for the healthy amounts of essential nutrients that one need (Institute of Medicine, 2006).

Table 5 shows how the IOPs in the access to the acceptable nutrition

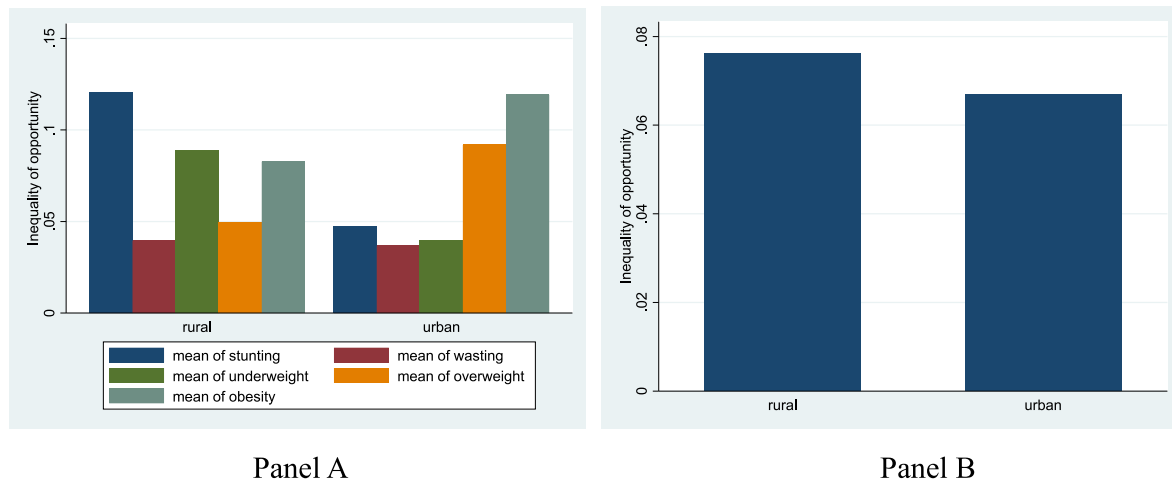


Fig. 4. Inequality of opportunity in children's nutritional outcomes by hukou.

Table 5
Inequality of opportunity in macronutrient intakes by hukou status.

	Rural			Urban		
	Carbohydrate	Fat	Protein	Carbohydrate	Fat	Protein
Panel A. Overall inequality of opportunity (%)						
IOP	27.48	17.47	14.45	8.91	7.61	7.96
Panel B. Decomposition (% of IOP)						
Age	0.87	1.75	18.88	5.94	22.64	4.18
Gender	0.78	0.54	1.36	0.13	7.61	0.32
Household size	7.96	10.37	2.93	3.26	6.91	5.03
Birth order	3.82	4.75	1.53	1.12	2.09	4.56
Region	7.17	7.36	22.58	18.14	15.88	35.41
Family background	24.86	24.74	31.48	21.74	28.62	18.55
Sanitation	16.71	14.65	12.67	26.57	1.95	13.97
Year effect	37.83	35.84	8.58	23.11	14.31	17.97
N	4706	4706	4706	2055	2055	2055

intake differ between the rural children and urban children. We find that the IOPs in probability for within the normal macronutrient intakes are much higher for rural children (ranging from 14.45% to 27.48%) compared to their urban counterparts (ranging from 7.61% to 8.91%). The results in Table 5 also suggest family background is the dominant factor contributing to IOP for both rural and urban children.

Another question worth investigating is whether the change of migration status (as a type of effort) will affect the opportunities of being in good nutritional status for the children. To answer this question, we conducted a simple counterfactual analysis. The method is presented in Appendix 3.

Table 6 compares the results between the original and counterfactual sample. Panel A shows the difference of the prevalence of stunting, wasting, underweight, overweight and obesity, indicating that the prevalence of stunting and underweight (obesity and overweight) are significantly lower (higher) for the counterfactual sample compared to

the original sample. This suggests that when rural children migrate to cities with their parents, they may be less likely to be stunting, but more likely to be obese. Panel B further shows the change of IOP after those rural children had moved to cities. Importantly, the IOPs in the five nutritional outcomes for the counterfactual sample are all more than 19% larger compared to those for the original sample. To be specific, the percentage change of IOPs range from 19.84% (stunting) to 55.75% (obesity).

5. Discussion and conclusion

Health inequality at birth implies that health inequality should be corrected during early childhood. This is important in promoting equal opportunities in health status and addressing inequality in other domains in later adulthood. This study investigates children's nutritional outcomes in China from the perspective of inequality of opportunity.

Table 6
Comparison between the original and counterfactual sample.

	Stunting	Wasting	Underweight	Overweight	Obesity
Panel A. Prevalence					
Original sample	0.100	0.051	0.051	0.075	0.107
Counterfactual	0.084	0.045	0.041	0.084	0.120
Difference	-0.016***	-0.006	-0.009*	0.009*	0.013**
Panel B. IOP (%)					
Original sample	11.49	3.64	7.92	6.90	9.13
Counterfactual	13.77	4.37	10.03	10.06	14.22
Difference	2.28	0.73	2.11	3.16	5.09
Percentage change	19.84	20.05	26.64	45.80	55.75

The study yields several findings. First, the inequality of opportunity in children's nutritional outcomes are significant in China. The IOPs range from 3.64% (wasting) to 11.49% (stunting). These results are relatively smaller than that in some other Asian countries shown in Aizawa (2019). They find the largest IOP in Pakistan as 21.7% and the smallest IOP in Maldives as 5.9%. As for the contribution of each of the circumstances, region plays a dominant role. This echoes Ding et al. (2021) who find that rural/urban and province of residence are the largest contributors to health inequality for the elderly. In addition, family background is also important in some cases. This finding is consistent with previous studies which documented the well-established intergeneration transmission of socioeconomic status from parents to children (Currie, 2011; Halliday et al., 2020). The mechanisms underlying this gradient may be due to differences in health-related choices and behaviors such as seeking health care and eating habits.

Second, we identify an increasing trend of IOP over years (with the only exception of 2011). The findings are consistent with Chen et al. (2014), revealing that Chinese children's average health status has improved from 1989 to 2009, but inequality has widened. In addition, we find that the IOPs in both under- and over-nutrition is the largest for those aged 6–10 years old. As previous studies have indicated, the income-health gradient becomes more pronounced as children grow older (Case et al., 2002). Goode et al. (2014) suggest that the family income-child health gradient among Chinese children increases with child age until the age of 12. Therefore, our study is also broadly in line with theirs. With respect to regional heterogeneity, our results indicate that the west region has the largest IOP in undernutrition while that for overnutrition is in eastern China. This finding is congruent with the strand of literature which suggests regional inequalities in child nutrition across China's east, middle and west regions (Chen et al., 2006).

Third, our results show that children with rural hukou have larger IOP in undernutrition compared to their urban counterparts, while the latter have larger IOP in overnutrition. This finding aligns with the widely documented literature on rural-urban disparities in child health in low- and middle-income countries (Paciorek et al., 2013; Srinivasan et al., 2013). Noticeably, urban children have higher IOPs in being overweight or obese, confirming the growing prevalence of overweight and obesity in urban China. The counterfactual analysis further reveals that if those rural children had migrated to cities with parents, it would decrease the prevalence of undernutrition but increase that for overnutrition. This may to some extent imply that urbanization has both positive and negative influence on population. The adverse consequences of urbanization and migration are evidenced by the branch of literature on health penalty for urbanization (Van de Poel et al., 2012). On one hand, urban population has easier access to health care facilities

and nutritious diets. On the other hand, as a result of rapid urbanization and industrialization, urban residents also face higher risk factors such as formatting unhealthy lifestyle and eating unhealthy diets. The latter may pose health threats—such as being overweight or obesity—for urban children, leading to a health penalty for migration and urbanization. Moreover, it is interesting to note that the IOP for the counterfactual full sample would increase by more than 19%. This may indicate that greater attention should be paid to inequality of opportunity in child nutrition when more rural Chinese children are expected to migrate to cities.

Our study has important policy implications. This study suggests that greater attention should be paid to IOP in nutritional status among Chinese children, childhood stunting in particular. Given that observed circumstances play a dominant role in explained inequality in child nutritional status, public health policies should pay special attention to inequitable circumstances disparities—urban and rural differentials and inequality in parental occupation and education—to effectively mitigate child nutrition inequality. Finally, as inequality of opportunity in child nutrition increases with age until reaching 10, various nutrition programs and interventions aiming at improving early childhood health and nutrition conditions (e.g. preschool free lunch program) are encouraged to achieve health equity in the long term. In the light of high persisting rates of wasting and the increasing trend of overweight among young children in many low- and middle-income countries, our estimates of inequality of opportunity provide a new perspective to researchers, policy makers and public health agencies in their efforts to address childhood nutrition inequality. Identifying factors that can be attributable to “circumstance” underlying the presence of child nutritional inequality is necessary to formulate appropriate policy interventions.

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Declaration of competing interest

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

Appendix 1. Methods

Step 1: Calculation of overall inequality of opportunity

Building on the IOP in health literature (Davillas and Jones, 2020), nutritional outcome (y_i) is a function of circumstances and efforts and efforts could also be influenced by circumstances. We can write:

$$y_i = a + bC_i + cE_i + u_i \quad (1)$$

$$E_i = d + eC_i + v_i \quad (2)$$

We can then obtain the reduced-form regression by substituting Equation (2) into Equation (1):

$$y_i = \alpha + \beta C_i + \varepsilon_i \quad (3)$$

where $\alpha = a + cd$, $\varepsilon = cv_i + u_i$, $\beta = b + ce$, which comprises both the direct impact of circumstances on nutritional outcomes and the indirect impact of circumstances through efforts; y_i is children's nutritional outcomes and C denotes the circumstance variables used in this study. Building on the concept of types, the main idea of calculating IOP is to suppress within-type inequality stemming from efforts. Using this regression-based method, we can obtain a smoothed distribution of nutritional outcomes $\{\hat{y}_i\}$, by replacing each y_i with the predicted values, as shown below:

$$\hat{y}_i = \hat{\beta}C_i \tag{4}$$

where $\hat{\beta}$ denotes the OLS estimates of the coefficient in Equation (3) and the counterfactual nutritional outcomes \hat{y}_i are the same for the individuals in each type where circumstances are identical. This framework can also be applied to cases where the nutrition variables are binary outcomes. In that case, we can use probit or logit model to estimate Equation (3). The default probit model is adopted in our regression wherever nutritional outcomes are binary.

This helps to eliminate within-type inequality and between-type inequality are kept as the measure for inequality of opportunity with an appropriate inequality index $I(\cdot)$. The absolute measure of IOP is therefore given by $I(\{\hat{y}_i\})$ while the corresponding relative measure of IOP is $I(\{\hat{y}_i\})/I(\{y_i\})$.

The choice of inequality index mainly depends on the type of the dependent variables and the scope of the analysis (Juárez and Soloaga, 2014). In the case of continuous variables, mean log deviation (MLD) and variance are widely used as the index of inequality for those with inherent scale (e.g., income) and those with arbitrary mean and dispersion (e.g., PISA score) (Ferreria and Gignoux, 2016). Nevertheless, for dichotomous and ordered independent variables, we adopt the modified dissimilarity index.

Step 2: Decomposition

The change in IOP when circumstance C is included in a subset R is defined by:

$$\Delta IOP_C = \sum_{R \subset C^T \setminus \{C\}} \frac{|r|!(t - |r| - 1)!}{t!} [IOP_{R \cup \{C\}} - IOP_R] \tag{5}$$

where C^T is the entire set of t circumstance variables and R is a subset of C^T where C is excluded and all other circumstance variables are included. IOP_R denotes the measure of inequality of opportunity for the subset of circumstances R and $IOP_{R \cup \{C\}}$ is the measure corresponding to the case where circumstance C is added to subset R . The contribution of circumstance C is therefore given by:

$$S_c = \frac{\Delta IOP_C}{IOP_C} \tag{6}$$

This procedure is computationally intensive, but two substantial advantages are worthy of attention. First, the sum of the Shapley values equals the total value, and second, this procedure is order independent (Juárez and Soloaga, 2014).

Appendix 2. Descriptions for constructing dummy variables for macronutrient intakes

The three dummies indicating whether relative macronutrient intakes belong to the acceptable macronutrient distribution range (AMDR) are calculated in three steps. First, the 3-day average intakes of each of three micronutrients—carbohydrate, fat and protein—were transferred into calories. Macronutrients can be utilized by the body for energy, with 1 g of fat yielding 9 kcal, and 1 g of protein and 1 g of carbohydrate each yielding 4 kcal (Zhang et al., 2015). Second, relative macronutrient intakes are expressed as the percentage of total energy intake (kcal) contributed by each of three micronutrients (kcal). Third, we compare relative macronutrient intakes with AMDR. As such, three dummy variables for carbohydrate, fat and protein are generated accordingly (Zhang et al., 2015).

Appendix 3. Methodology for counterfactual analysis

The counterfactual analysis is done in the following steps. First, we partition the sample into four groups: urban children (K_1 , living in cities with urban hukou), migrant children (K_2 , living in cities with parents with rural hukou), rural children (K_3 , living in rural areas with parents) and left-behind children (K_4 , living in rural areas without one or both parents). Based on this definition, we therefore examine how inequality of opportunity in nutritional outcomes would change if the rural and left-behind children chose to migrate to cities with their parents. To do this, the second step is to construct two sub-samples, with one consisting of K_2 and K_3 , and another one comprised of K_2 and K_4 . For each sub-sample, we treat K_2 as the control group, and the other K_3 or K_4 as the treatment group. That said, we construct a dummy variable indicting the treatment status:

$$D = \begin{cases} 0, & \text{if the child belongs to } K_2 \\ 1, & \text{if the child belongs to } K_3 \text{ or } K_4 \end{cases}$$

Following Gong et al. (2017), we then use logit model to examine how the circumstances affect children’s migration status for each of the sub-samples. Next, we apply propensity score matching method using nutritional status as the outcome variables. The predicted propensity score is used to select the matched children in the control group K_2 corresponding to the treatment group K_3 and K_4 respectively. We name these two new sub-samples as K_3^* and K_4^* . In this way, the efforts of children in the matched sub-sample K_3^* (or K_4^*) are identical to those in the control group K_2 because the sample of K_3^* (or K_4^*) is a sub-sample of K_2 ; the circumstances of children in K_3^* (or K_4^*) are identical to those in the treatment group because they have similar propensity score. This indicates that the nutritional status of the matched sub-samples K_3^* and K_4^* are the counterfactual nutritional outcomes if the children K_3 or K_4 chose to migrate with their parents. Building on this, we then compare the IOP for the original sample (a combination of K_1 , K_2 , K_3 and K_4) with that for the counterfactual sample (a combination of K_1 , K_2 , K_3^* and K_4^*). This helps to examine whether and how IOP would change if the children living in rural areas were to be migrant children.

Appendix 4. Inequality of opportunity in children's nutritional outcomes in various years

Table A4-1
Inequality of opportunity in children's nutritional outcomes in 1993

	Stunting	Wasting	Underweight	Overweight	Obesity
Panel A. Overall inequality of opportunity (%)					
IOP	11.99	3.90	9.55	5.94	5.23
Panel B. Decomposition (% of IOP)					
Age	11.80	38.42	22.81	0.31	23.90
Gender	2.23	1.45	3.87	5.88	0.52
Hukou	15.58	3.12	8.75	10.00	1.23
Household size	4.50	4.89	5.14	7.09	5.11
Birth order	2.44	6.69	5.33	3.67	28.66
Region	26.66	21.79	23.69	44.45	17.97
Family background	28.18	9.66	21.72	16.17	5.54
Sanitation	8.61	13.99	8.69	12.42	17.08
N	2312	2312	1506	2312	2312

Notes: we did not report inequality of opportunity in children's nutritional outcomes in 1991 because of missing hukou status information for the year 1991.

Table A4-2
Inequality of opportunity in children's nutritional outcomes in 2000

	Stunting	Wasting	Underweight	Overweight	Obesity
Panel A. Overall inequality of opportunity (%)					
IOP	10.51	6.31	6.60	7.15	9.34
Panel B. Decomposition (% of IOP)					
Age	3.01	43.34	0.07	12.51	31.64
Gender	0.78	1.13	4.94	19.60	8.68
Hukou	9.46	3.29	8.05	8.25	3.90
Household size	10.99	2.57	3.14	5.14	0.51
Birth order	8.31	9.36	1.56	3.57	0.12
Region	31.62	23.46	25.37	31.35	39.16
Family background	24.76	11.61	33.83	12.98	6.47
Sanitation	11.07	5.24	22.47	6.59	9.53
N	1360	1360	632	1360	1360

Table A4-3
Inequality of opportunity in children's nutritional outcomes in 2004

	Stunting	Wasting	Underweight	Overweight	Obesity
Panel A. Overall inequality of opportunity (%)					
IOP	11.53	3.70	7.18	9.74	9.44
Panel B. Decomposition (% of IOP)					
Age	6.19	5.46	2.58	1.82	4.17
Gender	0.45	2.27	0.12	0.85	16.04
Hukou	16.85	14.99	18.69	15.06	3.35
Household size	3.22	0.75	1.70	6.27	6.27
Birth order	4.74	2.08	2.40	9.14	1.07
Region	32.40	37.62	31.11	19.42	27.24
Family background	17.96	17.67	26.64	29.86	24.40
Sanitation	18.19	19.14	16.76	17.58	17.11
N	792	792	440	792	792

Table A4-4
Inequality of opportunity in children's nutritional outcomes in 2006

	Stunting	Wasting	Underweight	Overweight	Obesity
Panel A. Overall inequality of opportunity (%)					
IOP	9.84	5.34	10.67	7.63	15.95
Panel B. Decomposition (% of IOP)					
Age	9.94	0.78	3.04	0.41	8.46
Gender	0.21	0.30	1.03	2.96	17.69
Hukou	8.88	2.57	4.56	8.59	4.79
Household size	2.41	2.20	2.59	19.33	0.74
Birth order	4.75	3.80	1.58	12.01	0.91
Region	41.55	10.02	34.65	24.80	55.79
Family background	24.27	50.30	41.61	19.83	7.53
Sanitation	7.98	29.89	10.80	12.06	4.05
N	742	742	449	742	742

Table A4-5
Inequality of opportunity in children's nutritional outcomes in 2009

	Stunting	Wasting	Underweight	Overweight	Obesity
Panel A. Overall inequality of opportunity (%)					
IOP	9.99	7.68	14.12	11.22	13.89
Panel B. Decomposition (% of IOP)					
Age	4.20	9.37	15.74	38.10	21.41
Gender	6.46	8.50	3.87	4.62	4.03
Hukou	6.72	10.44	7.64	6.50	13.44
Household size	5.34	1.01	4.93	1.61	1.74
Birth order	10.84	0.86	4.73	4.82	7.56
Region	14.44	11.54	28.59	19.94	17.74
Family background	38.85	41.39	29.27	14.54	30.50
Sanitation	13.14	16.87	5.22	9.72	3.59
N	707	707	241	707	707

Table A4-6
Inequality of opportunity in children's nutritional outcomes in 2011

	Stunting	Wasting	Underweight	Overweight	Obesity
Panel A. Overall inequality of opportunity (%)					
IOP	6.32	5.39	3.45	10.64	11.75
Panel B. Decomposition (% of IOP)					
Age	6.01	2.01	13.97	9.75	4.88
Gender	2.32	2.06	9.40	3.17	6.07
Hukou	9.94	13.29	13.73	9.71	5.96
Household size	4.30	5.80	1.63	7.31	3.35
Birth order	6.70	7.57	1.62	8.05	5.84
Region	31.79	39.45	19.48	35.31	55.71
Family background	25.57	25.98	32.28	16.66	11.92
Sanitation	12.84	3.84	7.87	10.04	6.27
N	848	848	539	848	848

Appendix 5. Inequality of opportunity in children's nutritional outcomes for three age cohorts

Table A5-1
Inequality of opportunity in nutritional outcomes for 0–5 age cohort

	Stunting	Wasting	Underweight	Overweight	Obesity
Panel A. Overall inequality of opportunity (%)					
IOP	9.02	2.91	4.45	4.33	11.90
Panel B. Decomposition (% of IOP)					
Age	4.64	1.02	3.48	4.62	5.47
Gender	1.01	0.54	0.87	2.40	0.95
Hukou	11.01	2.09	7.48	5.81	2.81
Household size	2.85	6.06	1.45	18.38	1.38
Birth order	5.55	10.10	2.99	10.62	1.97
Region	28.08	50.22	25.20	11.82	31.46
Family background	20.33	8.94	32.99	10.47	8.43
Sanitation	11.41	4.72	17.66	11.00	2.35
Year effects	15.10	16.25	7.73	24.87	45.19
N	1584	1584	1584	1584	1584

Table A5-2
Inequality of opportunity in nutritional outcomes for 6–10 age cohort

	Stunting	Wasting	Underweight	Overweight	Obesity
Panel A. Overall inequality of opportunity (%)					
IOP	12.87	4.64	10.45	10.14	9.15
Panel B. Decomposition (% of IOP)					
Age	1.55	5.84	0.20	2.20	0.64
Gender	1.18	2.68	1.59	1.89	6.82
Hukou	10.33	10.00	8.28	11.10	16.52
Household size	3.64	2.34	7.04	4.55	1.98
Birth order	4.92	5.56	5.37	4.67	2.57
Region	17.68	39.69	24.27	30.90	28.53
Family background	22.24	3.86	23.99	16.93	11.58
Sanitation	12.19	3.95	11.84	8.96	4.42

(continued on next page)

Table A5-2 (continued)

	Stunting	Wasting	Underweight	Overweight	Obesity
Year effects	26.20	26.08	17.40	18.79	26.93
N	2416	2416	2416	2416	2416

Table A5-3

Inequality of opportunity in nutritional outcomes for 11–15 age cohort

	Stunting	Wasting	Underweight	Overweight	Obesity
Panel A. Overall inequality of opportunity (%)					
IOP	13.50	3.60	–	8.38	8.19
Panel B. Decomposition (% of IOP)					
Age	0.02	5.92	–	10.01	6.84
Gender	0.82	2.34	–	6.77	14.34
Hukou	10.53	8.18	–	10.89	1.82
Household size	7.88	9.11	–	3.09	0.65
Birth order	3.56	12.40	–	2.43	3.07
Region	19.54	21.77	–	28.07	14.60
Family background	30.20	13.03	–	13.77	9.18
Sanitation	9.79	4.63	–	14.05	4.53
Year effects	17.62	22.62	–	10.87	44.97
N	2761	2761	–	2761	2761

Notes: Data for underweight is unavailable for children aged 10 and above.

Appendix 6. Inequality of opportunity in children's nutritional outcomes in three regions**Table A6-1**

Inequality of opportunity in nutritional outcomes in the east region

	Stunting	Wasting	Underweight	Overweight	Obesity
Panel A. Overall inequality of opportunity (%)					
IOProwhead	7.88	3.35	3.62	7.18	10.98
Panel B. Decomposition (% of IOP)					
Age	1.38	25.43	3.01	21.68	19.61
Gender	1.85	4.45	2.61	2.81	15.86
Hukou	14.95	0.73	14.74	14.84	2.10
Household size	4.78	3.55	0.95	1.59	5.34
Birth order	11.61	6.33	1.82	2.53	11.34
Family background	20.37	31.06	34.10	13.08	11.90
Sanitation	20.92	5.85	18.81	24.05	2.64
Year effects	24.13	22.60	23.78	19.38	31.21
N	2139	2139	1118	2139	2140

Table A6-2

Inequality of opportunity in nutritional outcomes in the middle region

	Stunting	Wasting	Underweight	Overweight	Obesity
Panel A. Overall inequality of opportunity (%)					
IOP	7.06	4.15	6.34	5.43	12.23
Panel B. Decomposition (% of IOP)					
Age	2.17	46.73	20.76	1.93	11.35
Gender	0.26	0.06	0.06	11.91	1.54
Hukou	9.01	4.80	5.56	11.09	5.35
Household size	6.35	4.79	3.49	8.55	0.43
Birth order	3.02	0.48	1.17	11.25	1.88
Family background	24.17	11.42	34.71	22.35	11.62
Sanitation	9.48	17.21	13.46	10.95	6.96
Year effects	45.52	14.51	20.75	21.96	60.87
N	2490	2490	1433	2490	2490

Table A6-3
Inequality of opportunity in nutritional outcomes in the west region

	Stunting	Wasting	Underweight	Overweight	Obesity
Panel A. Overall inequality of opportunity (%)					
IOP	16.72	3.65	10.59	3.25	5.12
Panel B. Decomposition (% of IOP)					
Age	3.94	17.57	20.58	8.28	15.67
Gender	1.72	1.86	1.65	5.88	18.65
Hukou	11.89	11.85	8.71	8.27	1.82
Household size	1.72	9.60	2.04	14.72	1.85
Birth order	0.95	12.80	3.49	3.80	4.40
Family background	40.44	13.57	28.62	25.24	17.37
Sanitation	25.77	4.55	21.33	12.97	3.50
Year effects	13.48	28.21	13.58	20.81	36.72
N	2132	2132	1318	2132	2132

References

- Aizawa, T., 2019. Ex-ante inequality of opportunity in child malnutrition: new evidence from ten developing countries in Asia. *Econ. Hum. Biol.* 35, 144–161.
- Alderman, H., Hoddinott, J., Kinsey, B., 2006. Long term consequences of early childhood malnutrition. *Oxf. Econ. Pap.* 58, 450–474.
- Alesina, A., Angeletos, G.-M., 2005. Fairness and redistribution. *Am. Econ. Rev.* 95, 960–980.
- Almond, D., Currie, J., Duque, V., 2018. Childhood circumstances and adult outcomes: Act II. *J. Econ. Lit.* 56, 1360–1446.
- Aristides dos Santos, A.M., Perelman, J., Jacinto, P. de A., Tejada, C.A.O., Barros, A.J.D., Bertoldi, A.D., Matijasevich, A., Santos, I.S., 2019. Income-related inequality and inequity in children's health care: a longitudinal analysis using data from Brazil. *Soc. Sci. Med.* 224, 127–137.
- Asadullah, M.N., Mansoor, N., Randazzo, T., Wahhaj, Z., 2021. Is son preference disappearing from Bangladesh? *World Dev.* 140, 105353.
- Behrman, J.R., Rosenzweig, M.R., 2002. Does increasing women's schooling raise the schooling of the next generation? *Am. Econ. Rev.* 92, 323–334.
- Black, R.E., Morris, S.S., Bryce, J., 2003. Where and why are 10 million children dying every year? *Lancet* 361, 2226–2234.
- Black, S.E., Devereux, P.J., Salvanes, K.G., 2005. The more the merrier? The effect of family size and birth order on children's education. *Q. J. Econ.* 120, 669–700.
- Case, A., Lubotsky, D., Paxson, C., 2002. Economic status and health in childhood: the origins of the gradient. *Am. Econ. Rev.* 92, 1308–1334.
- Chang, Y., Zhai, F., Li, W., Ge, K., Jin, D., de Onis, M., 1994. Nutritional status of preschool children in poor rural areas of China. *Bull. World Health Organ.* 72, 105–112.
- Chen, K., Liu, C., Liu, X., Wang, Z., Luo, R., Li, S., Yu, Y., Alderman, H., 2021. Nutrition, cognition, and social emotion among preschoolers in poor, rural areas of South Central China: status and correlates. *Nutrients*.
- Chen, L., Wu, Y., Coyte, P.C., 2014. Income-related children's health inequality and health achievement in China. *Int. J. Equity Health* 13, 1–11.
- Chen, Z., Wood, E., Yan, Z., Yao, W., 2006. Inequality of child malnutrition in China: where you live matters. *World Econ.* 54–66 (In Chinese).
- Currie, J., 2011. Inequality at birth: some causes and consequences. *Am. Econ. Rev.* 101, 1–22.
- Currie, J., Moretti, E., 2003. Mother's education and the intergenerational transmission of human capital: evidence from college openings. *Q. J. Econ.* 118, 1495–1532.
- Davillas, A., Jones, A.M., 2020. Ex ante inequality of opportunity in health, decomposition and distributional analysis of biomarkers. *J. Health Econ.* 69, 102251.
- Deschenes, O., Wang, H., Wang, S., Zhang, P., 2020. The effect of air pollution on body weight and obesity: evidence from China. *J. Dev. Econ.* 145, 102461.
- Ding, L., Jones, A.M., Nie, P., 2021. Ex ante Inequality of Opportunity in Health among the Elderly in China: A Distributional Decomposition Analysis of Biomarkers. *Rev. Income Wealth*.
- Doorslaer, E. van, Koolman, X., 2004. Explaining the differences in income-related health inequalities across European countries. *Health Econ.* 13, 609–628.
- Ervin, P.A., Bubak, V., 2019. Closing the rural-urban gap in child malnutrition: evidence from Paraguay, 1997–2012. *Econ. Hum. Biol.* 32, 1–10.
- Ferreira, F.H.G., Gignoux, J., 2011. The measurement of inequality of opportunity: theory and an application to Latin America. *Rev. Income Wealth* 57, 622–657.
- Francesconi, M., Heckman, J.J., 2016. Child development and parental investment: introduction. *Econ. J.* 126, F1–F27.
- Ghosh, S., Sharma, S.K., Bhattacharya, D., 2020. Deciphering disparities in childhood stunting in an underdeveloped state of India: an investigation applying the unconditional quantile regression method. *BMC Publ. Health* 20, 1–21.
- Golley, J., Kong, S.T., 2018. Inequality of opportunity in China's educational outcomes. *China Econ. Rev.* 51, 116–128.
- Golley, J., Yixiao, Z., Meiyuan, W., 2019. Inequality of opportunity in China's labor earnings: the gender dimension. *China World Econ.*
- Gong, F., Li, Z., Lei, X., 2017. The impact of effort on the measurement of inequality of opportunity: measurement and comparison. *Econ. Res. J.* 3, 76–90 (In Chinese).
- Goode, A., Mavromaras, K., Zhu, R., 2014. Family income and child health in China. *China Econ. Rev.* 29, 152–165.
- Halliday, T.J., Mazumder, B., Wong, A., 2020. The intergenerational transmission of health in the United States: a latent variables analysis. *Health Econ.* 29, 367–381.
- Hatton, T.J., Sparrow, R., Suryadarma, D., van der Eng, P., 2018. Fertility and the health of children in Indonesia. *Econ. Hum. Biol.* 28, 67–78.
- Institute of Medicine, 2006. *Dietary Reference Intakes: the Essential Guide to Nutrient Requirements*. The National Academies Press, Washington, DC.
- Juárez, F.W.C., Soloaga, I., 2014. iop: estimating ex-ante inequality of opportunity. *Stata J.* 14, 830–846.
- Liu, H., Fang, H., Zhao, Z., 2013. Urban-rural disparities of child health and nutritional status in China from 1989 to 2006. *Econ. Hum. Biol.* 11, 294–309.
- Ngure, F.M., Reid, B.M., Humphrey, J.H., Mbuya, M.N., Pelto, G., Stoltzfus, R.J., 2014. Water, sanitation, and hygiene (WASH), environmental enteropathy, nutrition, and early child development: making the links. *Ann. N. Y. Acad. Sci.* 1308, 118–128.
- Paciorek, C.J., Stevens, G.A., Finucane, M.M., Ezzati, M., 2013. Children's height and weight in rural and urban populations in low-income and middle-income countries: a systematic analysis of population-representative data. *Lancet Global Health* 1, e300–e309.
- Rahman, A., 2019. Cultural norms and son preference in intrahousehold food distribution: a case study of two Asian rural economies. *Rev. Income Wealth* 65, 415–461.
- Roemer, J.E., 1998. *Equality of Opportunity*. Harvard University Press.
- Sharaf, M.F., Rashad, A.S., 2016. Regional inequalities in child malnutrition in Egypt, Jordan, and Yemen: a Blinder-Oaxaca decomposition analysis. *Health Econ. Rev.* 6, 1–11.
- Shi, X., 2019. Inequality of opportunity in energy consumption in China. *Energy Policy*.
- Singh, A., 2012. Inequality of opportunity in earnings and consumption expenditure: the case of Indian men. *Rev. Income Wealth* 58, 79–106.
- Srinivasan, C.S., Zanello, G., Shankar, B., 2013. Rural-urban disparities in child nutrition in Bangladesh and Nepal. *BMC Publ. Health* 13, 1–15.
- United Nations Children's Fund (UNICEF), World Health Organization, 2021. *International bank for reconstruction and development/the world bank. In: Levels and Trends in Child Malnutrition: Key Findings of the 2021 Edition of the Joint Child Malnutrition Estimates*. United Nations Children's Fund, New York.
- Van de Poel, E., O'Donnell, O., Van Doorslaer, E., 2007. Are urban children really healthier? Evidence from 47 developing countries. *Soc. Sci. Med.* 65, 1986–2003.
- Van de Poel, E., O'Donnell, O., Van Doorslaer, E., 2012. Is there a health penalty of China's rapid urbanization? *Health Econ.* 21, 367–385.
- Walker, S.P., Wachs, T.D., Grantham-McGregor, S., Black, M.M., Nelson, C.A., Huffman, S.L., Baker-Henningham, H., Chang, S.M., Hamadani, J.D., Lozoff, B., Gardner, J.M.M., Powell, C.A., Rahman, A., Richter, L., 2011. Inequality in early childhood: risk and protective factors for early child development. *Lancet* 378, 1325–1338.
- Weber, A., Darmstadt, G.L., Rao, N., 2017. Gender disparities in child development in the east Asia-Pacific region: a cross-sectional, population-based, multicountry observational study. *Lancet Child Adolesc. Heal.* 1, 213–224.
- 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.
- Yang, X., Gustafsson, B., Sicular, T., 2021. Inequality of opportunity in household income, China 2002–2018. *China Econ. Rev.* 69, 101684.
- Zhang, N., Bécares, L., Chandola, T., 2015. A multilevel analysis of the relationship between parental migration and left-behind children's macronutrient intakes in rural China. *Publ. Health Nutr.* 19, 1913–1927.
- Zhang, Y., Kang, L., Zhao, J., Song, P.Y., Jiang, P.F., Lu, C., 2021. Assessing the inequality of early child development in China - a population-based study. *Lancet Reg. Heal. - West. Pacific* 14, 100221.