Social Disadvantage and Child Health among China's Rural-Urban Migrant Households

Carl Lin, *Bucknell University and IZA*

Yana van der Meulen Rodgers, *Rutgers University*

Abstract

This study uses migrant household survey data from 2008 and 2009 to examine how social disadvantage among rural-urban migrant households is associated with the nutritional status of children. The measures of social disadvantage are based on China's hukou system of household registration – designed to limit domestic migration flows by denying public services in cities to migrants with rural registrations – and on gender bias that may harm women and girls. Results from fixed-effects regressions indicate that the hukou system has a negative association with children's weight-for-age Z-scores, even after controlling for household characteristics. Tests for gender-based disadvantage indicate that children in female-headed households do not experience a nutritional penalty relative to children in households headed by men, while girls do exhibit poorer nutritional status compared to boys. The Hausman–Taylor IV estimator is applied to account for unobservable heterogeneity including also time-invariant indicators and the results are consistent with the fixed effects regressions. Additional results from a standard Oaxaca decomposition, a detailed quantile decomposition based on recentered influence function (RIF) regressions, and a counterfactual distribution analysis all confirm that children who are left behind in rural villages – usually because of the oppressive hukou system – have poorer nutritional status than children who migrate with their parents, and the gaps are biggest at lower portions of the distribution.

Keywords: Rural-urban migration, China, children, health
JEL Classifications: I10, J61

Notes: Corresponding author is Carl Lin, Assistant Professor of Economics, Bucknell University, 1 Dent Drive, Lewisburg, PA 17837, USA. E-mail: carl.lin@bucknell.edu. We thank Ira Gang and seminar participants at the Confucius Institute of Rutgers University and the workshop "Challenges to Children's Welfare in Contemporary China" at University of Pennsylvania for their helpful comments.

I. Introduction

Insufficient food consumption and the lack of a healthy diet for children can result in unwanted weight loss, fatigue, headaches, poor mental health, and frequent illness. Childhood health in turn serves as an important determinant of an individual's health status in adulthood and of his or her likelihood of developing costly and debilitating health conditions. In addition, children's nutritional status and health are associated with performance in school and years of educational attainment, both of which serve as important predictors of future labor market outcomes, especially wages and occupational attainment. The literature provides strong evidence that relates childhood health and nutritional status to cognitive development, school performance, and future success in the labor market.[1] For example, Victora *et al.* (2008) conducted an extensive meta-analysis as well as their own analysis of data for five developing countries and found that that low height-for-age and weight-for-age at two years of age are associated with long-term impairment in educational attainment, school performance, adult height, productivity, and earnings. The authors concluded that nutritional deprivation among children is an important mechanism that can undermine the health outcomes of successive generations.

Children's nutritional status is affected by a number of factors that include environmental exposure, food intake, illnesses, and other external determinants that are influenced by socioeconomic status (Puffer and Serrano 1973). One of these determinants is parental employment, and a large body of work indicates that one of the most important channels through which parental employment affects child health and nutritional status is through the income that they earn.[2] Yet parents' participation in the labor market can entail a fundamental tradeoff. The income that parents earn contributes to the household's ability to purchase goods and services that improve children's health and nutritional status. However, parents' market-based work could reduce the quantity or quality of time spent caring for children, with potentially adverse effects on child well-being. Just like household income, time spent with children also affects the degree to which parents, and especially mothers, can engage in care practices that influence child nutrition and health.

This tradeoff between income from market-based work and time spent away from children can be heightened for parents who have migrated to urban areas and left their children behind in rural villages in the care of others. Parental remittances may improve children's nutritional status through the purchase of more nutritious foods and through housing improvements that are conducive to children's health. However, migrant parents are apart from their children and the quality of care from substitute care-providers may be inferior. Migrant parents who bring their children with them also face this tradeoff given the pressure that migrants face to work long hours in paid employment in order to stave off the risk of economic hardship that comes with rural-to-urban migration.

This study, to the best of our knowledge, is the first to examine how the employment and socioeconomic status of migrant parents in China relates to the nutritional status of their children – both children left behind and children who migrate with their parents. We are especially interested in how longstanding forms of social and economic disadvantage can filter through to the health of children in rural-urban migrant households. China constitutes an important case study not only because it is the world's most populous country that is experiencing the biggest internal migration flow ever (estimated at 245 million people in 2016 by National Bureau of Statistics of China), but also because it has tried to manage an enormous flow of rural to urban migration with an institutionalized system of social disadvantage known as the hukou that may have unintended consequences for children's well-being. In particular, the hukou is a household registration system based on either a rural or urban classification that depends mostly on birthplace of the household head and is very difficult to change. Moreover, many public services in urban areas are restricted to individuals with urban hukou only, thus excluding rural-to-urban migrants who still have their rural hukou and denying them access to public healthcare, schooling, and social services.

China is also known for its strong cultural preferences for sons, which is reflected in discrimination against girls in decisions about health care, schooling, and feeding. Sen (1989) drew attention to this "missing women" problem with evidence of unusually high male to female population ratios in Asia and North Africa. The preference for sons and this shortfall of women relative to men in the population can arise from a number of cultural, economic, and institutional factors that cause parents to treat boys in ways that favor their growth and development over girls. Parental behavior such as withholding healthcare when a girl is sick contributes to the selective neglect of "unwanted" girls and to their higher chances of nutritional deprivation and even mortality. The absence of social protection institutions for old age, relatively fewer employment opportunities for women, and strict family planning policies can reinforce the lower social value of women and the cultural preference for having sons (Das Gupta *et al.* 2003). Hence, young girls in China's migrant households may be more at risk for poor nutritional status than boys. The lower value of women, in turn, may contribute to relatively greater economic hardship for female-headed households compared to male-headed households that have migrated to China's urban areas if women face discrimination in the labor market and have more trouble finding a well-paying job than their male counterparts. A number of studies have documented persistent gender gaps in pay and employment in China's urban labor markets.[3]

This analysis utilizes data from the Longitudinal Survey on Rural Urban Migration in China (RUMiC), a rich dataset on migrant workers and their households that has detailed information on human capital indicators, socioeconomic status, food expenditures, and health. The data are used to examine the determinants of children's nutritional status, as measured by weight-for-age Z-scores (WAZ scores) and height-for-age Z-scores (HAZ scores). We are particularly interested in how the nutritional status of children in migrant households differs across four important dimensions of social disadvantage associated with China's rural to urban migration flows: (1) children in migrant households that fail to obtain an urban hukou compared to children in households that do secure an urban hukou; (2) children in female-headed households as opposed to children in male-headed households in a context where female migrant workers may have more trouble finding well-paying jobs due to gender discrimination in the labor market; (3) girl children as opposed to boy children in a context where son preference may lead parents to favor their boys over girls in allocating food and seeking healthcare; and (4) children who are left behind in rural villages in the care of others as opposed to children who migrate to urban areas with their parents. A battery of tests is used to clearly identify the links between social disadvantage and children's nutritional status, including ordinary least squares regressions, a Hausman-Taylor estimator (Hausman and Taylor 1981), a standard Oaxaca decomposition, and detailed quantile decompositions based on recentered influence function (RIF) regressions (Firpo *et al*. 2009; Fortin *et al*. 2011). Lastly, we estimate a set of counterfactual quantile treatment effects (Chernozhukov *et al*. 2013) by constructing a counterfactual scenario which captures what the WAZ or HAZ distribution would be if left-behind children were to live with their parents in cities.

II. Background: Disadvantage and Inequality in China

China's institutionalized form of migrant exclusion - the hukou system of household registration - favors households with an urban registration and discriminates against households with a rural registration in the allocation of resources and public services. In this hukou system, one's status is assigned at birth, is based simply on a rural versus urban categorization, and it is created administratively (Afridi *et al.* 2015). Upward mobility from a rural hukou to an urban hukou is notoriously difficult, although not impossible for people with specialized secondary or tertiary educations and for people who are members of the Chinese Communist Party (Wu and Treiman 2004).

The hukou system evolved gradually after the Communist revolution in 1949 as the government tried to control the flow of rural to urban migrants. Despite the government's efforts to stem this flow, the past few decades have seen an enormous surge of rural to urban migration in China, with some estimates that half of China's population now lives in urban areas, up from just one-fifth in the early 1980s. The majority of these urban migrants do not hold urban household registrations, which means they are denied access to health care, public education, pensions, and other public services. This form of exclusion places rural-to-urban migrants without an urban hukou at a distinct disadvantage relative to people who do have urban hukou.

A growing body of research indicates that China's urban migrants with a rural hukou are at considerable risk of being socially and economically disadvantaged in terms of access to jobs, subsidized products, education, and public services (Afridi *et al.* 2015; Chen and Feng 2013; Dreger *et al.* 2015). For example, even though schooling in China is compulsory and free for the first 9 years, public funding for schools is allocated according to the types of hukou that children hold and it is not transferable across administrative entities (Chen and Feng 2013). This feature of public school funding means that local schools in urban areas do not receive additional funds to educate migrant students who hold rural hukou. A substantial proportion of migrating children are thus forced to enroll in migrant schools, which began as informal schools to meet the needs of migrants in urban areas and have commonly been perceived as inferior to public schools. Evidence in Chen and Feng (2013, 2017) indicates that migrating children who enroll in migrant schools have lower standardized test scores in Chinese and math relative to students enrolled in public schools. Closely related, evidence in Zhang *et al.* (2015) indicates that school performance among migrating children is substantially worse than that of children of urban residents, just as there is a large difference between rural and urban children.

Another outcome of the hukou system is discrimination in the labor market, where urban migrants who hold rural hukou have more difficulty being hired into high-wage formal sector jobs, especially those in state-owned enterprises (Song 2014). To the extent that urban migrants with rural hukou are less likely to find high-wage employment, there are strong implications for their ability to send remittances back home, which in turn could impact the well-being of their children left behind. In particular, Hannum *et al.* (2014) find that children living in poverty in China's rural areas are more likely to experience food insecurity and be undernourished compared to children in wealthier households, and that food-insecure children in turn have lower literacy levels in the long term. Discrimination in the labor market can also worsen overall economic status, a result found in Yang (2013). This study finds that rural-urban migrants in China who do not have an urban hukou have substantially lower socioeconomic status compared to their locally-born counterparts and compared to urban-urban migrants, where socioeconomic status takes into account not only earnings and occupation but also access to social insurance and quality housing.

Our analysis of the hukou system, social disadvantage, and child health also builds on work in Mu and De Brauw (2015), Chen (2013), and Meng and Yamauchi (2015), each of which examine the nutritional status of children in China left behind in rural hometowns after one or both parents migrated to a city. Using data from the China Health and Nutrition Survey, Mu and De Brauw (2015) find that the income effect outweighs any detrimental effect of parental time away from children. In particular, the migration of at least one parent (where the gender of the migrating parent is not specified) is associated with an improvement in weight-for-age among children under the age of five, while there is no statistically significant effect on children's height-for-age. In contrast, Chen (2013) uses the same data to examine the effects of fathers' migration on children's body mass and finds no statistically significant effects. Meng and Yamauchi (2015) use different data – the RUMiC survey – and find that as the duration of the absence of mothers increases due to migration, the height-for-age and weight-for-age of rural children ages 15 and below decreases, while the duration of the absence of migrant fathers has a negative and statistically significant effect only on rural children's weight-for-age. Hence the evidence on whether parental migration boosts or harms nutritional status of children left behind in China's rural areas is inconclusive, and none of these previous studies examine migrating children in urban areas.

III. Data

To estimate the determinants of nutritional status among children in China's migrant households, we use data from the Rural-to-Urban Migrants Surveys for 2008 and 2009 from the Longitudinal Survey on Rural Urban Migration in China (RUMiC). The RUMiC was set up to investigate the patterns and effects of migration in China. The survey involves individual microdata jointly collected by researchers at the Australian National University, the University of Queensland, and the Beijing Normal University.[4] Figure 1 shows the 15 cities that are either provincial capitals or other major migrant-receiving cities in which the migrant household survey was taken. These cities are contained in nine provinces and three regions. The Eastern region contains Guangzhou, Dongguan, Shenzhen, Shanghai, Nanjing, Wuxi, Hangzhou, and Ningbo; the Central region includes Zhengzhou, Hefei, Luoyang, Bengbu, and Wuhan; and the Western region contains the two highly populated cities of Chengdu and Chongqing. The survey contains comprehensive information on a wide array of control variables that can affect measures of children's food consumption and nutritional status. The sample is restricted to children ages 15 and below who live in households that report household expenditures.[5] After deleting observations with missing values for any of the key variables in the analysis, our pooled dataset contains a total of 3,235 children, of whom 1,429 live with their parents in urban areas and 1,806 are left behind in the rural hometowns.[6] This imbalance between children who migrate with their parents versus those who are left behind is consistent with evidence in Mu and De Brauw (2015) that among Chinese households with urban migrants, migration of entire families is less common so many children are left behind.

Note that the RUMiC migrant survey contains no sample weights. Due to the largely incomplete official residential registration of migrants in cities, the most fundamental challenge of designing an unbiased sampling frame involves how to randomly sample the migrant population when lacking reliable information on the migrants' backgrounds and their distribution (Gong *et al.* 2008). Existing migrant surveys (for example, the China Urban Labour Survey conducted by China Academy of Social Sciences) nevertheless use administrative records of residential addresses as the basis for sampling. However, a large proportion of migrant workers in China live in their workplaces such as factory dormitories and construction sites, so the residential sampling framework is inevitably biased. The RUMiC survey addresses this issue by using a unique sampling frame based on information collected in a census of migrant workers at their workplaces, and the census is conducted in a number of randomly selected city grids within the defined city's boundary (IZA *et al.* 2014).[7]

We use data in the RUMiC on children's height and weight to specify children's nutritional status as height-for-age and weight-for-age Z-scores (standard deviation scores).[8] These measures both compare a child to a reference population. For population-based assessment, the Z-score is routinely considered to be the best system for analysis of anthropometric data and the best indicator of malnutrition. The Z-score specifies the relevant anthropometric value as a number of standard deviations above or below the reference median of the U.S. Centers for Disease Control Reference Population for children of the same gender (CDC 2000). The formula for calculating the Z-score is: Z-score = (observed value - median value of the reference population) / standard deviation of the reference population by gender. We used the CDC growth charts as a standard rather than the World Health Organization (WHO) growth charts – another common reference population – because the CDC comparison group is a more suitable reference group as argued in Meng and Yamauchi's (2015) analysis of child health outcomes in China. That said, our regression results do not change substantively when the WHO standards are used.

Sample means, presented in Table 1, indicate that on average, children from migrant families who live with their parents have higher WAZ and HAZ scores than their counterparts who are left behind. Among the control variables, the sample means indicate that a very high percent of children in migrant households have a rural hukou (97 percent), and this figure is even higher for children who are left behind in rural villages.[9] More than a quarter of migrating children are in female-headed households, and this proportion is even higher for children living with their parents. Fewer than half of the children are girls, and for the final key indicator of disadvantage, about 56 percent of children in migrant households are left behind in rural villages. Of particular interest among the other control variables is the food share in total consumption spending: on average, migrating children live in households that spend between 3 and 4 percent of their total consumption budgets on food. Also of note is the average weekly hours of work by the household head, which is considerably higher for the parents of children left behind (35) compared to the parents who still live with their children (30). Consistent with published statistics on gender gaps in schooling, on average mothers have about two years less schooling than fathers, a gap that is larger for the parents of left-behind children and smaller for parents who live with their children. Also consistent with published statistics, most household heads identify their ethnicity as Han, the dominant ethnic group in China.

Looking closer at the differences in anthropometric measures between children of migrant families who live with their parents and those who are left behind, Figure 2 depicts kernel density estimates for the weight-for-age and height-for-age Z-scores. Each curve shows the distribution of Z-scores around zero (where the observed value for a particular child equals the median value for the reference group). Both panels in Figure 2 depict weighted kernel densities using standard bandwidths that are selected non-parametrically. Panel A shows that the WAZ distribution for children left behind is generally to the left of the distribution for children living with their parents, indicating that left-behind children are at greater risk of nutritional deprivation as measured by their weight-for-age. The difference in the two distributions is even larger for the HAZ distributions. Since height-for-age is considered a longer-term measure of nutritional deprivation, the figure suggests that migration decisions that entail leaving children behind can have long-lasting negative repercussions for the children's nutritional status.

IV. Empirical Methodology

OLS Regressions with Fixed Effects

The effects of parental characteristics such as employment and education on children's health outcomes and nutritional status commonly accrue through higher socioeconomic status, which in turn operates through a set of "proximate determinants" of health that directly influence child health outcomes and nutritional status (Mosley and Chen 1984). The proximate determinants include fertility factors, environmental hazards, feeding practices, injury, and utilization of health services. At the household level, income and wealth are linked to child well-being through the effects that purchased goods and services have on the proximate determinants of child health. Employed parents bring income into the household, which allows for greater household expenditures. Greater income and assets directly increase the ability of households to purchase or access clean water, clothing, adequately-ventilated housing, fuel for proper cooking, safe storage of food, personal hygiene items, health services, and sufficient quantities of nutritious foods. These items all serve as direct input into children's health and nutritional status. In other words, these proximate determinants are the mechanisms by which socioeconomic status affects child health. This framework's emphasis on socioeconomic status in influencing children's nutritional status is consistent with findings in Yip *et al.* (1992) that poor growth status among Asian children—as measured by low birth weight, stunting (low height-for-age), and wasting (low weight-for-height)—is mostly associated with nutritional and health determinants rather than genetic factors.

We start the empirical analysis with a fixed-effects regression analysis of the determinants of children's nutritional status. The estimation equation is specified as follows:

$$Y_{ijt} = b_1 D_{ijt} + b_2 X_{ijt} + b_3 J_j + b_4 T_t + e_{ijt} \tag{1}$$

The notation Y_{ijt} denotes the nutritional status of child i in region j in year t, alternatively measured as weight-for-age Z-scores and height-for-age Z-scores; the variable D is an indicator of social disadvantage, alternatively measured by whether or not the household has a rural hukou, whether or not the household has a female household head, whether or not the child is a girl, and whether or not the child lives with their parents. The matrix X represents household-level controls, including the prestige ranking of the household head's primary occupation, a set of dummy variables for consumption expenditure quartiles, the share of food expenditures in total consumption expenditures, the usual weekly hours worked by the household head, mother's years of schooling, father's years of schooling, age of the household head, a dummy variable for household head is of the Han ethnic group (the dominant ethnic group in China), and height of the household head. Note that the occupational prestige variable is a ranking from 0 to 25 (from lowest to highest prestige) for the 25 occupation categories in the RUMiC data based on the occupational prestige scores in Li (2005). Depending on specifications, the matrix X also includes village-level and city-level characteristics. The village-level controls measure public facility accessibility in the villages where the parents migrated from, including distance to the nearest primary school, junior high school, and bus station, and whether or not the hometown has a health clinic. The city-level controls measure economic conditions in the cities where the migrant households currently live, including GDP per capita and the number of hospitals, doctors, and employed workers.[10]

Also in equation (1), J represents region-level fixed effects, and T denotes year fixed effects.[11] The equation is estimated for all children in migrant families as well as separately for children living with their parents and children left behind. Because the survey records multiple children per household as separate observations, we correct the standard errors for clustering at the level of the household.

Efficient Generalized Instrumental Variables − Hausman-Taylor Estimator

In the literature, the standard methods to account for endogeneity issues caused by unobservable heterogeneity are the fixed-effects and the random-effects estimators. However, there are two major shortcomings with these models. First, practitioners are left to make an 'all or nothing' decision regarding whether the fixed-effects or the random-effects estimator should be applied. Second, in cases where it is more reasonable to assume that the unobserved individual effects are related to the explanatory variables, estimation of time-invariant explanatory variables is not possible as the fixed-effects estimator needs 'within' variation (i.e. individuals' variation over time).

To overcome these shortcomings, Hausman and Taylor (1981) – hereafter HT − proposed a model where some of the explanatory variables are related to the individual-specific effects while others are not, permitting the identification for estimates of the time-invariant explanatory variables, such as education; and, finally, to avoid the complexity associated with the choice of suitable instruments since the individual means over time of all the included regressors can serve as valid instruments. A nice feature of the HT estimator is that external instruments are not required; instruments are derived from within the model (explained subsequently). Additionally, the variance-covariance structure can be taken into account to obtain estimators that are more efficient. The underlying HT model is as follows:

$$Y_{ijt} = \beta_1 X_{1,ijt} + \beta_2 X_{2,ijt} + \gamma_1 Z_{1,ij} + \gamma_2 Z_{2,ij} + \alpha_i + e_{ijt} \tag{2}$$

where $X_{1,ijt}$ is a vector of exogenous, time-varying variables which are assumed to be uncorrelated with the unobserved individual effects α_i; $X_{2,ijt}$ is a vector of endogenous variables which also are time-varying but correlated with α_i; $Z_{1,ijt}$ is a vector of exogenous, time-invariant variables which are assumed to be uncorrelated with the individual effects α_i; and $Z_{2,ijt}$ is vectors of endogenous time-invariant variables that are correlated with α_i; whereas e_{ijt} is the stochastic error term. We also include region fixed effects and year fixed effects in the estimations.

Using the HT estimator comes with at least two strong advantages. First, there is no need for model-external instruments: $X_{1,ijt}$ and $Z_{1,ij}$ serve as their own instruments, $X_{2,ijt}$ is instrumented by its deviation from individual means, $X_{2,ijt} - \bar{X}_{2,ij}$, and $Z_{2,ij}$ is instrumented by the individual average of $X_{1,ijt}$, that is $\bar{X}_{1,ij}$. If the model is identified, i.e. as long as there are at least as many time-varying exogenous variables as there are time-invariant endogenous variables, the resulting FGLS estimator is consistent and efficient (Greene, 2008). The second advantage is that, as mentioned, this method allows estimating the effects of time-invariant explanatory variables that may be correlated with the individual specific effects.

Oaxaca Decomposition, Quantile Regressions, and Quantile Gap Decompositions

In the next part of the analysis, for both indicators of nutritional status, the gap between left-behind children and children who migrate with their parents is decomposed into an explained portion and an unexplained portion. Specifically, using a fairly standard application of the Oaxaca-Blinder procedure, we decompose the WAZ score gap Δ (and alternatively the HAZ score gap) between left-behind children and children who migrate with their parents into a portion explained by average group differences in observed characteristics and a residual portion that is unexplained (Oaxaca 1973; Blinder 1973). This decomposition is expressed in vector-matrix form as

$$\begin{aligned}\Delta_t = \overline{\mathbf{Y}}_t^{LB} - \overline{\mathbf{Y}}_t^{MC} &= \overline{\mathbf{X}}_t^{LB}\mathbf{b}_t^{LB} - \overline{\mathbf{X}}_t^{MC}\mathbf{b}_t^{MC} \\ &= \underbrace{(\overline{\mathbf{X}}_t^{LB} - \overline{\mathbf{X}}_t^{MC})\mathbf{b}_t^{LB}}_{\substack{\text{explained gap} \\ \text{(characteristics effect)}}} + \underbrace{(\mathbf{b}_t^{MC} - \mathbf{b}_t^{LB})\overline{\mathbf{X}}_t^{MC}}_{\substack{\text{unexplained gap} \\ \text{(coefficient effect)}}} \qquad (3)\end{aligned}$$

where the bar denotes the sample average, t is the year, and the superscripts LB and MC denote left-behind children and migrating children who live with their parents. The explained gap is the portion of the gap attributed to differences between the two groups of children in observed characteristics as measured by the control variables in equation (3), and the unexplained gap is the portion attributed to differences in the coefficients on those variables. We further decompose the first and second terms of equation (3), a method henceforth referred to as the detailed decomposition, to measure the contribution of every variable in the equation.[12]

To perform a similar decomposition at different quantiles of the WAZ score and HAZ-score distributions, we utilized the unconditional quantile regression technique as developed in Firpo *et al.* (2009). Using this technique, we trace the entire distribution of WAZ scores and HAZ scores by steadily increasing the percentile in increments of 10 from 0 to 100. Let $q_t^{LB}(\tau)$ and $q_t^{MC}(\tau)$ denote the τth quantile of the WAZ and HAZ distributions for left-behind children and migrating children who live with their parents, respectively. The quantile gap, $\Delta_t(\tau)$, can be defined as

$$\Delta_t(\tau) = q_t^{LB}(\tau) - q_t^{MC}(\tau). \tag{4}$$

Firpo *et al*. (2009) and Fortin *et al*. (2011) show that one can decompose the quantile gaps by replacing the dependent variable *Y* with a recentered influence function (RIF) in unconditional quantile regressions. Suppose the quantile of interest is $q(\tau)$. Then the recentered influence function, $RIF_{ijt}(\tau)$, is defined as

$$RIF_{ijt}(\tau) = q(\tau) + [I(Y_{ijt} \geq q(\tau)) - (1-\tau)] / f(q(\tau)), \tag{5}$$

where $I(\bullet)$ is the indicator function (= 1 if $Y_{ijt} \geq q(\tau)$; = 0 otherwise), and $f(q(\tau))$ is the WAZ (HAZ) density evaluated at the τth quantile. The notation $I(Y_{ijt} \geq q(\tau))$ is simply a dummy indicating whether a WAZ (HAZ) observation is above a given quantile, and the other terms in equation (5) are constants. Hence running a regression of $RIF_{ijt}(\tau)$ on the X variables is essentially running a linear probability model for whether the WAZ (HAZ) score for a given observation is above or below the quantile. The coefficients obtained from the RIF-regressions are the same as those from linear probability models except that the RIF-regression coefficients must be divided by the density $f(q(\tau))$. The RIF-regression equation is essentially the same as the OLS regression in equation (1), such that:

$$RIF_{ijt}(\tau) = b_1 D_{ijt} + b_2 X_{ijt} + b_3 J_j + b_4 T_t + e_{ijt}. \quad (6)$$

The coefficients have the same interpretation insofar as they indicate the effects of the independent variables on the unconditional quantile. In the case of these unconditional quantile regressions, the RIF-regression for the mean is just a standard OLS regression, and the decomposition at the mean is a conventional Oaxaca decomposition (Firpo *et al*. 2009; Fortin *et al*. 2011). The *b* coefficients in the RIF-regression are interpreted as effects of the independent variables on unconditional quantiles.[13]

Counterfactual Distributions: Quantile Treatment Effects

The last stage of the empirical analysis is to estimate a set of counterfactual quantile treatment effects. Conceptually, we want to construct a counterfactual scenario which captures what the WAZ or HAZ distribution would be if left-behind children were to live with their parents in cities. In this case, the treatment effect is simply the difference between the counterfactual and the observed distributions. That is, the quantile treatment effect equals the counterfactual distribution minus the observed distribution, where the observed distribution is replaced by the fitted distribution during the estimation.

One approach to the counterfactual analysis uses the technique developed in DiNardo *et al*. (1996), which is based on a semiparametric method that reweights observations using propensity scores in order to obtain counterfactual densities. Chernozhukov *et al*. (2013) complements this method by providing standard errors for the estimates of the treatment effects. The use of standard errors—which was previously ignored in many decomposition analyses in economics—allows us to unravel the economic significance of diverse effects from the statistical uncertainty. The analysis below applies the Chernozhukov *et al*. (2013) method and defines the counterfactual group as migrating children who live with parents (coded as "1" in the procedure). The reference group is left-behind children (coded as "0").

As such, we define the conditional distribution functions $F_{Y_0|X_0}(y|x)$ and $F_{Y_1|X_1}(y|x)$ as the stochastic assignment of WAZ (or HAZ) scores to children with characteristics x for group 0 and 1, respectively. Suppose $F_{Y\langle 0|0\rangle}$ and $F_{Y\langle 1|1\rangle}$ are the observed WAZ (or HAZ) distribution functions of for group 0 (left-behind children) and 1 (migrating children who live with their parents), then $F_{Y\langle 0|1\rangle}$ represent the counterfactual distribution function—the one that would have prevailed for children living with their parents if they had faced left-behind children's characteristics $F_{Y_0|X_0}$. That is, the counterfactual distribution is defined as:

$$F_{Y\langle 0|1\rangle}(y) := \int_{\chi_1} F_{Y_0|X_0}(y|x)dF_{X_1}(x). \tag{7}$$

We construct the counterfactual distribution by integrating the conditional distribution of WAZ (or HAZ) scores for group 0 with respect to the distribution of characteristics for group 1. And the quantity is well-defined if χ_0 (the support of group 0's characteristics) contains the support of group 1 such that $\chi_1 \subseteq \chi_0$. Intuitively, this condition implies that every migrating child who lives with their parents can be matched with a left-behind child with the same characteristics.

Next, given the counterfactual distribution in equation (7), we are interested in the effect of changing the conditional distribution of the outcomes for a given group. The distribution effect (DE) can be written as:

$$\Delta^{DE}(y) = F_{Y\langle 1|1\rangle}(y) - F_{Y\langle 0|1\rangle}(y). \tag{8}$$

More often we are interested in quantiles:

$$Q_{Y\langle k|l\rangle}(\tau) = \inf\{y : F_{Y\langle k|l\rangle}(y) \geq u\},\ 0 < \tau < 1.$$

where $k \in \{0,1\}$ and $l \in \{0,1\}$. Analogous to equation (8), the quantile treatment effect (QTE) on the treated is:

$$QTE(\tau) = Q_{Y\langle 1|1\rangle}(\tau) - Q_{Y\langle 0|1\rangle}(\tau). \tag{9}$$

In estimating these conditional distributions of WAZ and HAZ scores, we run the quantile regressions 300 times to approximate the conditional distributions, and the variances are estimated by bootstrapping the results 500 times.[14]

To make inferences about the estimated quantile counterfactual distributions, we follow Chernozhukov *et al*. (2013) and test five null hypotheses: 1) the parametric conditional model is correctly specified; 2) the change in the distribution of the covariates has no effect at all such that $QTE(\tau) = 0$ for all τ; 3) all *QTEs* are equal to the median treatment effect such that $QTE(\tau) = QTE(.5)$ for all τ; 4) the counterfactual distribution first order stochastically dominates the observed distribution such that $QTE(\tau) > 0$ for all τ; and 5) the observed distribution first order stochastically dominates the counterfactual distribution such that $QTE(\tau) < 0$ for all τ. We report both P-values of the Kolmogorov-Smirnov and the Cramer-von-Misses-Smirnov test statistics for these hypothesis tests by WAZ and HAZ scores.

V. Results and Discussion

Fixed-Effects Results

Table 2 reports the fixed-effects estimates for the determinants of the child anthropometric measures that include the four indicators of social disadvantage as well as a full set of socioeconomic status variables and household characteristics. One of the most striking results is that even after controlling for the full set of SES variables and household characteristics, the rural hukou variable has a negative and statistically significant relationship with migrating children's weight-for-age Z-scores. In particular, children in migrant families who still have a rural hukou have a WAZ score that is, on average, 0.33 points lower than children in migrant families who have an urban hukou. This coefficient is not only statistically significant, but it is also relatively large in magnitude. Interestingly, the second column of results shows that most of this estimate is coming from children who continue to live with their parents, while the rural hukou does not appear to matter as much for children who are left behind. The only coefficient estimate that is larger in magnitude is for Han ethnicity. The estimates show that children from families where household heads are members of the majority Han ethnicity have a WAZ score that is, on average, 0.45 points lower than their ethnic minority counterparts, with most of this effect coming from children who are left behind.[15]

For the next indicator of social disadvantage – female-headed household – children from female-headed households do not appear to experience any drawback in terms of their WAZ scores as originally hypothesized. The first three columns show that female headship has a fairly small and statistically insignificant association with children's weight-for-age Z-scores. This result may arise from the counteracting effect of mothers tending to spend higher proportions of additional resources on investments in children's human capital compared to fathers (Quisumbing and Maluccio 2003, Doss 2006). Although improvements in household income may benefit all members, resources concentrated in the hands of women may do more for children than those concentrated in the hands of men (Thomas 1997). Women's control over financial resources has well-documented effects on human-capital outcomes for themselves and their children through cooperatively-bargained processes. These beneficial effects may be dominating any negative effects that women experience from gender discrimination in the labor market.

Although we don't see an association when it comes to the sex of the household head and children's WAZ scores, we do see a penalty for girl children: on average, a girl has a WAZ score that is 0.20 points lower compared to a boy – a penalty that is about the same for children living with their parents and children who are left behind. Because these Z-scores are constructed from reference population averages that are gender-specific, the lower WAZ scores do not reflect physiological norms in which boys weigh more than girls. Rather, girls are exhibiting lower WAZ scores for some other reason that could be related to China's traditional practices and views around son preference.

Our fourth indicator of social disadvantage is whether or not children from migrant families are left behind in their rural villages or live with their parents in urban areas. Not surprisingly, results in Table 2 indicate a substantial health penalty for being left behind as opposed to living with one's parents. Children from migrant families who are left behind in the care of other family members or friends in rural areas have WAZ scores that are 0.18 points lower than children who migrate with their parents to urban areas.

Several of the control variables have a negative and statistically significant relationship with children's WAZ scores. In particular, children whose parents work longer hours tend to have lower WAZ scores. This result reflects the tradeoff associated with market-based work: time spent by parents working in the labor market contributes to household income but takes away time spent caring for children, which could have a deleterious effect on their health. Age of the household head also has a negative and statistically significant association with children's WAZ scores. Counteracting these detrimental influences are positive relationships between children's WAZ scores and the occupational prestige ranking of the household head, mother's schooling, and height of the household head. The positive and statistically significant coefficient of mother's schooling on children's weight-for-age scores is consistent with findings in numerous studies for China and other countries that maternal education is an important positive determinant of child health (Boyle *et al.* 2006; Chen and Li 2009).

Not all of these conclusions hold for height-for-age scores, the longer-term indicator of children's nutritional status. One of the main differences is that holding a rural hukou no longer appears to be relevant for children's HAZ scores. Thus we conclude that children pay a cost in terms of nutritional status in the shorter term if their parents fail to obtain an urban hukou, but in the longer term the households are resilient and children do not suffer a penalty as measured by lower HAZ scores. In contrast, what does matter for children's HAZ scores is household headship. Children in migrant families headed by a woman have, on average, a height-for-age Z-score that is 0.59 points higher than children from migrant families with male household heads. This coefficient is large and statistically significant at the 1% level, and this association holds for the sub-samples of children living with their parents and children left behind. Most likely this result reflects previous findings in the literature that on the margin, financial resources in the hands of women have a larger impact on children's health and household budget allocations toward child investments as compared to financial resources in the hands of men. These previous findings would explain why children in our Chinese sample have higher height-for-age Z-scores if they are members of female-headed households as compared to male-headed households.

Some of the conclusions made for WAZ scores also hold for HAZ scores. In particular, girl children still experience a penalty in their HAZ scores relative to boys, although the result is only statistically significant for the sample of children who live with their parents. Another similar conclusion is that children who are left behind experience a substantial health penalty as compared to children who live with their parents, with a HAZ score differential of 0.32 points. The positive associations with maternal education and with height of the household head also hold for children's

HAZ scores, and these associations hold for both children who live with their parents as well as children who are left behind.

Results of Oaxaca Decomposition and Decomposition of Quantile Gaps

The next stage of the analysis entailed Oaxaca and quantile decompositions of the gap in WAZ and HAZ scores between left-behind children and children who live with their parents. Table 4 reports these gaps as the score for left-behind children minus the score for children living with their parents. The table indicates that at the mean and at all percentiles of the WAZ and HAZ distributions, children who live with their parents have higher WAZ and HAZ scores than children left behind. These group differences are statistically significant at all percentiles except for the WAZ scores in the top half of the distribution. At the mean, most of the WAZ gap is explained by differences in coefficients (61 percent), while most of the HAZ gap is explained by differences in characteristics (62 percent). This result implies that steps taken to improve the socioeconomic status of migrant households (as measured by the variables included is the matrix of observed characteristics) will do more to close the nutritional status gap in the longer term (as indicated by HAZ scores) than in the shorter term (as indicated by WAZ scores).

Looking more closely at the quantile decomposition results for the WAZ scores, Table 4 shows that the total WAZ gaps become smaller as one moves up along the distribution. This closing of the gap occurs primarily due to smaller explained gaps between the two groups of children, as indicated by the column of results for gaps due to characteristics (1). Intuitively, left-behind children who are higher up the distribution of WAZ scores suffer less of a health penalty from relative deficiencies in household characteristics. This conclusion can also be seen in Figure 3, which plots changes along the distribution in the total WAZ-score gaps, explained gaps (due to characteristics), and unexplained gaps (due to coefficients) between left-behind children and children who live with their parents.

In the case of HAZ scores, Table 4 and Figure 4 shows that while the total gap does get smaller as one moves up along the percentiles, changes in the size of the explained gap and the unexplained gap do not always move in the same direction. While the explained gap (the portion due to observed characteristics) shrinks as one moves across higher percentiles of the distribution, the size of the unexplained gap (the portion due to coefficients) fluctuates across the distribution. Hence left-behind children in higher percentiles of the HAZ-score distribution are experiencing smaller overall gaps relative to children who live with their parents, and this relative improvement occurs due to their observed household characteristics as well as the returns to those characteristics.

Table 5 presents results for the detailed decompositions of the mean differences in WAZ and HAZ scores between left-behind children and children who live with their parents. In the case of the WAZ-score gap, the table shows that most of the gap – just over 60 percent – is explained by coefficients rather than observed productivity characteristics. Of the gap that is explained by characteristics, having a rural hukou is one of the most important determinants of the gap, accounting for about one quarter of the aggregate effect. Other important contributors to the mean gap between the two groups of children are occupational rank of the household head, the usual hours worked by the household head, and mother's years of education. In the case of HAZ scores, the unexplained portion of the mean gap is considerably smaller, at less than 40 percent. Of the gap that is explained by characteristics, having a rural hukou matters less in explaining the overall gap as compared to the WAZ score decomposition. Other characteristics that play an important role in explaining the mean gap are living in a female-headed household, living in a relatively wealthy household, and mother's years of education.

The detailed quantile decompositions based on RIF-regressions for the total, explained, and unexplained gaps between the child groups indicate a number of interesting patterns for WAZ scores and HAZ scores. Table 6 (WAZ scores) and Table 7 (HAZ scores) report the aggregated effects of social disadvantage indicators, household-level controls, village and city controls, and year and region fixed effect. The full detailed quantile decomposition results are reported in the Appendix. One of the most important results for the WAZ-score gaps is that the characteristics effect from the gap in social disadvantage indicators ranges from about .03 to .04 points and is statistically significant for most quantiles except the upper tail of the distribution. As shown in the appendix, much of this gap is coming from having a rural hukou. The characteristics effect for household-level controls matters even more than social disadvantage at the lower end of the distribution but then ceases to be statistically significant from the 40th percentile onward. Although the coefficient effects in aggregate tend to be larger than the characteristic effects in most quantiles, there is no clear pattern as to which category of indicators contributes the most to the aggregate coefficient effect. For example, the coefficients effect for social disadvantage indicators is the only portion of the unexplained WAZ gap that is statistically significant at the 30th and 80th percentiles, while this changes to the village controls at the 50th and 70th percentiles.

One of the most important results for the HAZ-score gaps in Table 6 is that the characteristics effect from the gap in social disadvantage indicators ranges from about .04 to .06 points and is statistically significant for all quantiles except the very bottom of the distribution. As shown in the appendix, much of this gap is coming from living in a female-headed household, which remains a statistically significant part of the overall gap along most quantiles of the distribution. The characteristics effect for household-level controls has a substantially larger share in the aggregate effect compared to the social disadvantage indicators for every quantile of the distribution and is precisely estimated in all but one quantile (the 80th). Similarly, the coefficients effect for household-level controls is also larger in magnitude compared to the social disadvantage indicators, but the estimated effect is not always precisely estimated.

Results of Counterfactual Distributions

The final set of results is found in Table 8 and Figure 5, which report the counterfactual quantile treatment effects for WAZ and HAZ scores. As indicated by these results, the treatment effects are not statistically significant for the WAZ scores along most parts of the quantile distribution. The treatment effects are only significant at the bottom tail of the WAZ distribution, at the 10th and the 20th percentiles. One can infer from the graph that overall, the counterfactual curve does not shift very much. However, if those left-behind children at the bottom tail of the WAZ distribution were to live with their parents, their short-term nutritional status would improve. This counterfactual treatment effect does not apply for children above the 30th percentile.

In contrast, the treatment effects for the HAZ scores are statistically significant along the entire quantile distribution. We do not reject the null hypotheses that our parametric conditional model is correctly specified and the counterfactual quantile processes have constant effects. In addition, we reject the null that our model has no effect for all quantiles. This conclusion is evident from Figure 6 with the apparent shift of the counterfactual curve to the right. One could argue based on this counterfactual analysis that left-behind children would be better off in the long run (in term of their height-for-age) if they were to live with their parents in cities.

VI. Policy Lessons

This study, the first to examine China's rural-urban migrant households and the nutritional status of both children left behind as well as children who migrate with their parents, has found that China's institutionalized form of trying to limit migrant flows has a detrimental impact on the health of children. In particular, the hukou system of household registration – in which many public social services in China's cities are accessible only to residents with an urban household registration – has a negative and statistically significant association with children's weight-for-age Z-scores, even after controlling for a full set of socioeconomic status indicators and household characteristics. This indicator is a measure of short-term nutritional deprivation in which children are deprived of sufficient calories to exhibit substantial weight loss relative to the benchmark reference group. This relative deprivation for children whose parents do not hold an urban hukou is exhibited mostly for children who migrate with their parents; the result is not precisely estimated for children who are left behind. The urban hukou does not appear to have a relationship with height-for-age Z-scores – an indicator of longer-term nutritional status – after controlling for household socioeconomic status and composition, suggesting that rural-urban households are resilient in the longer term and are able to adjust to their new urban lives without their children exhibiting more permanent signs of reduced height due to insufficient caloric intake.

We also found substantial health penalties for WAZ and HAZ scores among children who are left behind in rural villages in the care of others, relative to children who migrate with their parents. These penalties are particularly large for children at lower ends of the WAZ and HAZ percentile distributions. Our counterfactual distribution analysis showed that these left-behind children would be better off in terms of their HAZ scores if they were to join their parents in the city. Finally, in our tests for penalties arising from gender, we found that children in female-headed households do not appear to suffer from any nutritional deprivation relative to children in households headed by men as originally hypothesized. However, girl children do exhibit lower HAZ and WAZ scores compared to boy children, a finding that is consistent with previous findings of son preference in China.

Examining the well-being of children in China's urban migrant households can offer powerful lessons for other developing countries that are experiencing rapid rural-to-urban migration and urbanization. Other countries may not have the same formal structure of constraints imposed on rural-to-urban migrants, but if their urban infrastructures are unable to keep up with the influx of new people, then children in migrant households may face similar risks of economic hardship and poor nutritional status. Overall our results point to the importance of revising the hukou system so that children who migrate to urban centers with their parents are not suffering from denial of public services and economic hardship that arise from their rural hukou status. Improving the accessibility of public services in urban areas for rural-urban migrants will also make it more likely that parents bring their children with them rather than leave them behind, thus mitigating another disadvantage for child health caused by China's inequitable system of household registration. Results from this study also support the implementation and enforcement of a number of other policy interventions, particularly those that support migrant parents' roles as caregivers of young children at the same time that they are employed in productive market-based activities in urban areas. Of particular importance is a transformative approach that boosts the remunerative value and security of migrants' jobs, improves the compatibility of market work with child care, and promotes skills development.

Improving the pecuniary returns that rural-urban migrants receive for their jobs in the form of wages at par with or exceeding the minimum wage, greater job security, and improved terms of employment will have a direct bearing on their employment decisions. Policy measures to achieve these goals are already embedded in China's national labor standards that cover formal sector workers, but the policies are enforced consistently across establishments. Measures such as safe workplace conditions, overtime pay, and paid benefits, although potentially costly to implement, promote lower turnover rates, improve well-being for workers, and contribute to extended firm-specific tenure. These measures need to be provided to a broader range of migrant workers by removing exemptions, promoting awareness of benefit availability, and strengthening enforcement efforts. That said, a substantial number of rural-urban migrants work in low-pay or unpaid jobs that are not covered by national labor standards or escape enforcement. In addition to enforcing labor standards in paid jobs that are supposedly covered by national labor laws, a related policy goal is to create more wage-employment and productive self-employment opportunities for migrant workers through policy reforms that incentivize opportunities to switch from low-paid work in marginally productive activities to more remunerative work in productive activities.

In addition, public support of out-of-home child care services helps to relieve the time and budgetary constraints that migrant workers experience. Public support for early education programs also directly benefits those children who otherwise could be receiving inferior-quality care from alternative providers, and it could substantially reduce the number of children who are left behind in rural villages when their parents migrate to urban centers. Public support of child care services also promotes higher levels of educational attainment among older children, especially girls, who otherwise might be withdrawn from school to care for younger siblings.

Policies to promote skill development will not only help migrants to secure productive employment opportunities, they will also help to build the capacity to meet development needs in the overall economy. Promoting skills development includes improving the quality of education for both boys and girls. Although China has worked to close its overall gender gap in educational attainment, there are still imbalances in the quality of the educations that young people are getting, and these imbalances are particularly severe between urban-born children and rural-born children. Moreover, depending on the types of activities in which migrant workers choose to engage, public support of vocational training can also be useful in preparing migrants for better-paying jobs. Finally, to better reach workers in the informal sector and in the outer reaches of urban areas, specially-designed training programs, such as those that are community-based or geographically mobile, can provide training opportunities to migrants who otherwise remain unreached by standard education and training initiatives.

Finally, it is imperative that the government try to stem migration flows by closing the rural-urban income gap. Relatively greater poverty, lower rates of wage-employment, poor infrastructure, and lower educational attainment in the rural sector reflect long-term patterns and support the argument that gains in prosperity since the late 1970s when the Chinese economy embarked on its rapid growth trajectory have not been evenly distributed (Rozelle 1996; Xu 2011). Policy reforms to address these disparities include investment in rural infrastructure and policies to strengthen the economic links between China's urban and rural areas as a means to reducing rural poverty and the rural–urban income gap that may have left rural households behind. Furthermore, improvements in the design of China's public safety net, including more spending to meet needs as well as better responsiveness to changing household circumstances, will help more people move from and stay out of poverty. Evidence indicates that although enrollment in primary school is nearly universal among young children, there is large attrition in the rate of children continuing onto secondary school, especially for girls living in rural areas (Connelly and Zheng 2003). Policy reforms that improve access to schools, the quality of education, and incentives such as free lunch programs so that children remain in school will go a long way to reduce these regional and gender disparities. Improved health and nutrition policies in rural areas such as vitamin supplement interventions will also help to improve school performance and reduce attrition (Luo *et al.* 2012; Zhou *et al.* 2015). Policies of this nature lend themselves to win-win situations in terms of being both pro-rural sector as well as pro-growth.

Bibliography

Afridi, Farzana, Sherry Xin Li, and Yufei Ren. 2015. “Social Identity and Inequality: The Impact of China's Hukou System,” *Journal of Public Economics* 123: 17-29.

Akgüç, Mehtap, Corrado Giulietti, and Klaus F. Zimmermann. 2014. “The RUMiC Longitudinal Survey: Fostering Research on Labor Markets in China,” *IZA Journal of Labor & Development* 3 (1): 1-14.

Alderman, Harold, John Hoddinott, and Bill Kinsey. 2006. “Long Term Consequences of Early Childhood Malnutrition,” *Oxford Economic Papers* 58 (3): 450-474.

Bhattacharya, Jayanta, Janet Currie, and Steven Haider. 2004. “Poverty, Food Insecurity, and Nutritional Outcomes in Children and Adults,” *Journal of Health Economics* 23 (4): 839-862.

Blinder, Alan. 1973. “Wage Discrimination: Reduced Form and Structural Estimates,” *Journal of Human Resources* 8 (4): 436-455.

Boyle, Michael, Yvonne Racine, Katholiki Georgiades, Dana Snelling, Sungjin Hong, Walter Omariba, Patricia Hurley, and Purnima Rao-Melacini. 2006. “The Influence of Economic Development Level, Household Wealth and Maternal Education on Child Health in the Developing World,” *Social Science & Medicine* 63 (8): 2242–2254.

Centers for Disease Control and Prevention (CDC). 2000. *Clinical Control Charts*. Atlanta, GA: CDC.

Chernozhukov, Victor, Iván Fernández-Val, and Blaise Melly. 2013. “Inference on Counterfactual Distributions,” *Econometrica* 81 (6): 2205-68.

Chen, Joyce. 2013. “Identifying Non-Cooperative Behavior among Spouses: Child Outcomes in Migrant-Sending Households,” *Journal of Development Economics* 100 (1): 1-18.

Chen, Yuanyuan, and Shuaizhang Feng. 2013. “Access to Public Schools and the Education of Migrant Children in China,” *China Economic Review* 26: 75-88.

Chen, Yuanyuan, and Shuaizhang Feng. 2017. “Quality of Migrant Schools in China: Evidence From a Longitudinal Study in Shanghai,” *Journal of Population Economics* doi:10.1007/s00148-016-0629-5.

Chen, Yuyu, and Hongbin Li. 2009. “Mother’s Education and Child Health: Is There a Nurturing Effect?” *Journal of Health Economics* 28 (2): 413-426.

Chi, Wei, and Bo Li. 2014. "Trends in China's Gender Employment and Pay Gap: Estimating Gender Pay Gaps with Employment Selection," *Journal of Comparative Economics* 42 (3): 708-725.

Chowa, Gina, David Ansong, and Rainier Masa. 2010. "Assets and Child Well-Being in Developing Countries: A Research Review," *Children and Youth Services Review* 32 (11): 1508-1519.

Connelly, Rachel, and Zhenzhen Zheng. 2003. "Determinants of School Enrollment and Completion of 10 to 18 Year Olds in China," *Economics of Education Review* 22 (4): 379-388.

Currie, Janet. 2009. "Healthy, Wealthy, and Wise: Socioeconomic Status, Poor Health in Childhood, and Human Capital Development," *Journal of Economic Literature* 47 (1): 87–122.

Currie, Janet, and Wanchuan Lin. 2007. "Chipping Away at Health: More on the Relationship between Income and Child Health," *Health Affairs* 26 (2): 331–344.

Das Gupta, Monica, Jiang Zhenghua, Li Bohua, Xie Zhenming, Woojin Chung, and Bae Hwa-Ok. 2003. "Why is Son Preference so Persistent in East and South Asia? A Cross-Country Study of China, India and the Republic of Korea," *Journal of Development Studies* 40 (2): 153-187.

DiNardo, John, Nicole M. Fortin, and Thomas Lemieux. 1996. "Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach," *Econometrica* 64 (5): 1001-44.

Dong, Xiao-yuan, and Paul Bowles. 2002. "Segmentation and Discrimination in China's Emerging Industrial Labor Market," *China Economic Review* 13 (2): 170-196.

Doss, Cheryl. 2006. "The Effects of Intrahousehold Property Ownership on Expenditure Patterns in Ghana," *Journal of African Economies* 15 (1): 149-180.

Dreger, Christian, Tongsan Wang, and Yanqun Zhang. 2015. "Understanding Chinese Consumption: The Impact of Hukou," *Development and Change* 46 (6): 1331-1344.

Fang, Tony, Morley Gunderson, and Carl Lin. 2016. "The Use and Impact of Job Search Procedures by Migrant Workers in China," *China Economic Review* 37: 154-165.

Firpo, Sergio, Nicole M. Fortin, and Thomas Lemieux. 2009. "Unconditional Quantile Regressions," *Econometrica* 77 (3): 953-973.

Gardeazabal Javier, and Arantza Ugidos. 2004. "More on Identification in Detailed Wage Decompositions," *The Review of Economics and Statistics* 86: 1034-1036.

Gong Xiaodong, Sherry Tao Kong, Shi Li, and Xin Meng. 2008. "Rural-Urban Migrants: A Driving Force for Growth," in Wing Thye Woo and Song Ligang (eds.) *China's Dilemma: Economic Growth, the Environment and Climate Change*. Asia Pacific Press: 110–152.

Greene, Willaim. H. 2008. *Econometric analysis*. Prentice Hall, Upper Saddle River, NJ.

Gustafsson, Björn, and Sai Ding. 2009a. "Villages Where China's Ethnic Minorities Live," *China Economic Review* 20: 193-207.

Gustafsson, Björn, and Sai Ding. 2009b. "Temporary and Persistent Poverty Among Ethnic Minorities and the Majority in Rural China," *Review of Income and Wealth* 55: 588-606.

Gustafsson, Björn, and Shi Li. 2000. "Economic Transformation and the Gender Earnings Gap in Urban China," *Journal of Population Economics* 13 (2): 305-329.

Gustafsson, Björn, and Shi Li. 2003. "The Ethnic Minority-Majority Income Gap in Rural China during Transition," *Economic Development and Cultural Change* 51 (4): 805-822.

Hannum, Emily, Jihong Liu, and Edward Frongillo. 2014. "Poverty, Food Insecurity and Nutritional Deprivation in Rural China: Implications for Children's Literacy Achievement," *International Journal of Educational Development* 34: 90-97.

Hausman, Jerry A. and William E. Taylor. 1981. "Panel data and unobservable individual effects," *Econometrica*, 49: 1377-1398.

Horrace William, and Ronald Oaxaca. 2001. "Inter-industry Wage Differentials and the Gender Wage Gap: An Identification Problem," *Industrial and Labor Relations Review* 54: 611-618.

Institute of Labor Economics (IZA), Australian National University, University of Queensland, and Beijing Normal University. 2014. Longitudinal Survey on Rural Urban Migration in China (RUMiC) 2008–2009. International Data Service Center of IZA (IDSC). Version 1.0. doi:10.15185/izadp.7680.1.

Jann, Ben. 2008. "The Blinder-Oaxaca Decomposition for Linear Regression Models," *The Stata Journal* 8 (4): 453-479.

Kong, Sherry Tao. 2010. "Rural–Urban Migration in China: Survey Design and Implementation," in Xin Meng, Chris Manning, Li Shi, and Tadjuddin Noer Effend (eds.) *The Great Migration: Rural–Urban Migration in China and Indonesia*. Edward Elgar Publishing: 135–150.

Li, Chunlin. 2005. "Prestige Stratification in the Contemporary China: Occupational Prestige Measures and Socio-Economic Index," *Sociological Research* 2: 74-102 (in Chinese).

Luo, Renfu, Yaojiang Shi, Linxiu Zhang, Chengfang Liu, Scott Rozelle, Brian Sharbono, Ai Yue, Qiran Zhao, and Reynaldo Martorell. 2012. "Nutrition and Educational Performance in Rural China's Elementary Schools: Results of a Randomized Control Trial in Shaanxi Province," *Economic Development and Cultural Change* 60 (4): 735-772.

Meng, Xin, and Chikako Yamauchi. 2015. "Children of Migrants: The Impact of Parental Migration on Their Children's Education and Health Outcomes," IZA Discussion Paper No. 9165.

Mosley, W. Henry, and Lincoln C. Chen. 1984. "An Analytical Framework for the Study of Child Survival in Developing Countries," *Population and Development Review* 10 (Supplement): 25–45.

Mu, Ren, and Alan De Brauw. 2015. "Migration and Young Child Nutrition: Evidence from Rural China," *Journal of Population Economics* 28 (3): 631-657.

National Bureau of Statistics of China (various years). *China Statistical Yearbook.* Beijing: China Statistics Press.

Oaxaca, Ronald 1973. "Male-Female Differentials in Urban Labor Markets," *International Economic Revie*w 14 (3): 693-709.

Ouyang, Yusi and Per Pinstrup-Andersen. 2012. "Health Inequality between Ethnic Minority and Han Populations in China," World Development 40 (7): 1452-1468.

Puffer, R. R., and C. V. Serrano. 1973. *Patterns of Mortality in Childhood*. World Health Organization, Washington, DC.

Quisumbing, Agnes, and John Maluccio. 2003. "Resources at Marriage and Intrahousehold Allocation: Evidence from Bangladesh, Ethiopia, Indonesia and South Africa," *Oxford Bulletin of Economics and Statistics* 65 (3): 283-327.

Rodgers, Yana. 2011. *Maternal Employment and Child Health: Global Issues and Policy Solutions*. Northampton, MA, and London: Edward Elgar Publishing.

Rozelle, Scott. 1996. "Stagnation Without Equity: Patterns of Growth and Inequality in China's Rural Economy," *The China Journal* 35: 63-92.

Sen, Amartya. 1989. "Women's Survival as a Development Problem," *Bulletin of American Academy of Arts and Sciences* 18 (2):14–29.

Song, Yang. 2014. "What Should Economists Know about the Current Chinese Hukou System?" *China Economic Review* 29: 200-212.

Thomas, Duncan. 1997. "Incomes, Expenditures, and Health Outcomes: Evidence on Intrahousehold Resource Allocation," in Lawrence Haddad, John Hoddinott, and Harold Alderman (eds.), *Intrahousehold Resource Allocation in Developing Countries*. Washington, DC: IFPRI, 142-164.

Victora, Cesar, Linda Adair, Caroline Fall, Pedro Hallal, Reynaldo Martorell, Linda Richter, and Harshpal Singh Sachdev. 2008. "Maternal and Child Undernutrition: Consequences for Adult Health and Human Capital," *The Lancet* 371 (9609): 340–357.

Wu, Xiaogang, and Xi Song. 2014. "Ethnic Stratification amid China's Economic Transition: Evidence from the Xinjiang Uyghur Autonomous Region," *Social Science Research* 44: 158-172.

Wu, Xiaogang, and Donald Treiman. 2004. "The Household Registration System and Social Stratification in China: 1955–1996," *Demography* 41 (2): 363-384.

Xiu, Lin, and Morley Gunderson. 2015. "Occupational Segregation and the Gender Earnings Gap in China: Devils in the Details," *International Journal of Manpower* 36 (5): 711-732.

Xu, Chenggang. 2011. "The Fundamental Institutions of China's Reforms and Development," *Journal of Economic Literature* 49 (4): 1076-1151.

Yang, Juhua. 2013. "Social Exclusion and Young Rural-Urban Migrants' Integration into a Host Society in China," *The ANNALS of the American Academy of Political and Social Science* 648 (1): 52-69.

Yip, Ray, Kelley Scanlon, and Frederick Trowbridge. 1992. "Improving Growth Status of Asian Refugee Children in the United States," *Journal of the American Medical Association* 267 (7): 937–940.

Yun, Myeong-Su. 2005. "A Simple Solution to the Identification Problem in Detailed Wage Decompositions," *Economic Inquiry* 43: 766-772.

Zhang, Dandan, Xin Li, and Jinjun Xue. 2015. "Education Inequality between Rural and Urban Areas of the People's Republic of China, Migrants' Children Education, and Some Implications," *Asian Development Review* 32 (1): 196–224.

Zhang, Xiaowei. 2008. "Market Reforms and Han–Muslim Variation in Employment in the Chinese State Sector," *World Development* 36 (11): 2341-2352.

Zhou, Chengchao, Sean Sylvia, Linxiu Zhang, Renfu Luo, Hongmei Yi, Chengfang Liu, Yaojiang Shi et al. 2015. "China's Left-Behind Children: Impact of Parental Migration on Health, Nutrition, and Educational Outcomes," *Health Affairs* 34 (11): 1964-1971.

Table 1. Sample Statistics

Characteristics	All Children		Left-Behind Children		Children with Parents	
	Mean	S.D.	Mean	S.D.	Mean.	S.D.
Outcome variables						
Weight-for-Age Z-score (WAZ)	.254	1.523	.160	1.568	.372	1.455
Height-for-Age Z-score (HAZ)	-.535	1.883	-.797	1.882	-.205	1.831
Key indicators of disadvantage						
Household has rural hukou	.973	.162	.997	.058	.943	.231
Female-headed household	.288	.453	.269	.444	.311	.463
Child is a girl	.433	.496	.431	.495	.435	.496
Child left behind	.558	.497	1.000	.000	.000	.000
Household level controls						
Occupational rank HH head	14.088	6.418	13.477	6.391	14.860	6.371
Bottom consumption quartile	.216	.411	.349	.477	.048	.213
2nd consumption quartile	.240	.427	.271	.445	.199	.400
3rd consumption quartile	.271	.444	.236	.425	.315	.465
Top consumption quartile	.274	.446	.144	.351	.438	.496
Food share in total consumption	3.445	1.428	3.657	1.530	3.178	1.236
Usual weekly hours worked HH head	32.793	36.103	34.977	35.087	30.033	37.176
Mother's years of education	6.141	4.055	5.148	4.376	7.397	3.197
Father's years of education	7.977	3.370	7.572	3.690	8.490	2.835
Age of HH head	35.023	5.200	34.907	5.120	35.169	5.297
HH head has Han ethnicity	.982	.134	.986	.119	.977	.150
Height of HH head (cm)	166.697	6.872	166.793	6.823	166.576	6.934
Village/Rural hometown information						
Distance between hometown and the nearest bus station (km)	14.518	22.891	13.813	21.328	15.410	24.704
Distance between hometown and the nearest primary school (km)	1.961	4.319	1.844	3.779	2.109	4.915
Distance between hometown and the nearest junior high school (km)	4.466	7.516	4.549	7.414	4.361	7.644
Hometown has health clinic	.894	.308	.895	.307	.893	.309
City level controls						
GDP per capita (log)	7.990	.970	8.133	.919	7.809	1.003
Number of hospitals	242.69	223.89	258.65	228.95	222.52	215.71
Number of doctors (thous.)	18.281	10.504	19.412	10.406	16.848	10.456
Number of employed workers (thous.)	2901.1	1709.8	3112.7	1776.0	2633.7	1582.9
No. observations	3,235		1,806		1,429	

Note: Sample includes children under the age of 16 years.

Table 2. OLS Estimates for Determinants of Child Anthropometric Measures

	Weight-for-Age Z-scores			Height-for-Age Z-scores		
	All Children	Children with Parents	Left-Behind Children	All Children	Children with Parents	Left-Behind Children
Social disadvantage indicators						
Rural hukou	-.334**	-.313*	-.108	-.208	-.218	-.088
	(.158)	(.167)	(.316)	(.228)	(.238)	(.549)
Female-headed HH	.108	.085	.191	.591***	.629***	.583***
	(.100)	(.140)	(.148)	(.126)	(.179)	(.182)
Child is a girl	-.202***	-.184**	-.222***	-.102	-.181*	-.033
	(.054)	(.078)	(.073)	(.071)	(.106)	(.095)
Child left behind	-.184***			-.322***		
	(.067)			(.088)		
Household level controls						
Occup. rank of HH head	.009*	.012**	.003	-.005	-.001	-.003
	(.004)	(.006)	(.006)	(.005)	(.008)	(.008)
2nd consumption quartile	.058	.002	.074	.051	.661*	-.056
	(.087)	(.243)	(.099)	(.115)	(.369)	(.124)
3rd consumption quartile	.017	.044	-.034	.165	.691*	.092
	(.092)	(.240)	(.109)	(.124)	(.367)	(.139)
Top consumption quartile	-.105	-.121	-.044	.139	.650*	.140
	(.099)	(.238)	(.135)	(.136)	(.365)	(.176)
Food share in consumption	.016	.044	.002	-.005	.044	-.035
	(.020)	(.035)	(.025)	(.026)	(.044)	(.032)
Usual hours worked (week)	-.007***	-.007***	-.006**	-.001	.001	-.002
	(.002)	(.003)	(.003)	(.002)	(.003)	(.003)
Mother's years of education	.018**	.032**	.012	.041***	.062***	.034**
	(.009)	(.015)	(.011)	(.011)	(.019)	(.014)
Father's years of education	.007	-.005	.009	.006	-.005	.004
	(.009)	(.015)	(.013)	(.012)	(.021)	(.016)
Age of HH head	-.069***	-.069***	-.066***	.008	.003	.012
	(.006)	(.008)	(.009)	(.007)	(.011)	(.010)
HH head has Han ethnicity	-.452**	-.305	-.581**	-.126	-.387*	.122
	(.176)	(.216)	(.271)	(.268)	(.230)	(.479)
Height of HH head	.024***	.024***	.025***	.035***	.036***	.036***
	(.006)	(.009)	(.009)	(.008)	(.012)	(.010)
Village level controls	Yes	Yes	Yes	Yes	Yes	Yes
City level controls	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.099	.126	.087	.059	.046	.034
No. observations	3,235	1,429	1,806	3,235	1,429	1,806

Note: Standard errors, in parentheses, are clustered at the household level. The notation *** is p <0.01, ** is p <0.05, * is p <0.10. All regressions include regional and year fixed effects. Children are under the age of 16.

Table 3. Hausman-Taylor Estimates for Determinants of Child Anthropometric Measures

	Weight-for-Age Z-scores		Height-for-Age Z-scores	
	Children with Parents	Left-Behind Children	Children with Parents	Left-Behind Children
Social disadvantage indicators				
Rural hukou	-0.266*	0.358	-0.126	-0.690
	(0.159)	(0.249)	(0.198)	(1.159)
Female-headed HH	1.456***	1.732***	1.482*	0.884*
	(0.430)	(0.317)	(0.763)	(0.502)
Child is a girl	-0.985*	-0.232	-0.562***	-0.510
	(0.605)	(0.435)	(0.214)	(0.582)
Selected household characteristics				
Occup. rank of HH head	0.014**	0.001	-0.000	-0.001
	(0.007)	(0.009)	(0.007)	(0.007)
Age of HH head	-0.059***	-0.047***	0.008	0.013
	(0.012)	(0.011)	(0.015)	(0.012)
Mother’s years of education	0.019	-0.012	0.052***	0.028
	(0.017)	(0.014)	(0.020)	(0.019)
Father’s years of education	0.006	0.065***	0.003	0.017
	(0.017)	(0.020)	(0.021)	(0.024)
Height of HH head	0.072***	0.082***	0.073*	0.045**
	(0.026)	(0.015)	(0.040)	(0.021)
Robust overidentifying restrictions Test				
Sargan-Hansen statistic	20.080	15.668	26.143§	33.247**
P-value	[0.328]	[0.548]	[0.097]	[0.011]
Village level controls	Yes	Yes	Yes	Yes
City level controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes
No. observations	1,429	1,806	1,429	1,806

Note: Standard errors, in parentheses, are clustered at the household level. The notation *** is $p < 0.01$, ** is $p < 0.05$, * is $p < 0.10$. All regressions include regional and year fixed effects. Children are under the age of 16.

Table 4. Mean and Quantile Decompositions of Differences in WAZ and HAZ Distributions between Left-Behind Children and Children Who Live with Their Parents

Mean/ Quantile(τ)	Weight-for-Age Z scores (WAZ)			Height-for-Age Z scores (HAZ)		
	Raw difference	Due to (1) Characteristics	Due to (2) Coefficients	Raw difference	Due to (1) Characteristics	Due to (2) Coefficients
	-.211***	-.083**	-.128***	-.592***	-.367***	-.225***
Mean	(.053)	(.033)	(.043)	(.066)	(.038)	(.055)
	[100]	[39.34]	[60.66]	[100]	[61.99]	[38.01]
	-.536***	-.240***	-.296***	-.564***	-.521***	-.043
.10	(.089)	(.050)	(.073)	(.150)	(.084)	(.125)
	[100]	[44.71]	[55.29]	[100]	[92.37]	[7.63]
	-.362***	-.136***	-.226***	-.801***	-.509***	-.292***
.20	(.114)	(.041)	(.058)	(.114)	(.066)	(.095)
	[100]	[37.52]	[62.48]	[100]	[63.55]	[36.45]
	-.365***	-.155***	-.211***	-.663***	-.430***	-.233***
.30	(.064)	(.038)	(.052)	(.093)	(.053)	(.077)
	[100]	[42.34]	[57.66]	[100]	[64.85]	[35.15]
	-.172***	-.082**	-.090*	-.773***	-.470***	-.303***
.40	(.059)	(.036)	(.048)	(.084)	(.049)	(.069)
	[100]	[47.74]	[52.26]	[100]	[60.81]	[39.19]
	-.280***	-.113***	-.167***	-.582***	-.394***	-.188***
.50	(.058)	(.036)	(.047)	(.077)	(.046)	(.063)
	[100]	[40.22]	[59.78]	[100]	[67.76]	[32.24]
	-.066	-.039	-.027	-.558***	-.318***	-.240***
.60	(.059)	(.037)	(.048)	(.075)	(.044)	(.062)
	[100]	[58.83]	[41.17]	[100]	[56.96]	[43.04]
	-.054	-.032	-.023	-.549***	-.297***	-.252***
.70	(.069)	(.042)	(.056)	(.080)	(.047)	(.066)
	[100]	[58.36]	[41.64]	[100]	[54.04]	[45.96]
	-.008	-.027	.020	-.339***	-.225***	-.114
.80	(.089)	(.053)	(.073)	(.087)	(.052)	(.074)
	[100]	[359.79]	[-259.79]	[100]	[66.35]	[33.65]
	-.011	.077	-.088	-.366***	-.245***	-.122
.90	(.123)	(.072)	(.102)	(.101)	(.055)	(.089)
	[100]	[-707.74]	[807.74]	[100]	[66.75]	[33.25]

Note: Robust standard errors in parenthesis. Shares of contribution to the raw difference in brackets. Number of quantile regressions estimated is 300. Total number of observations is 3235, whereas the numbers of observations in group 0 (migrating children live with parents) and in group 1 (left-behind children) are 1429 and 1806, respectively. The notation *** is p <0.01.

Table 5. Detailed Decomposition of Mean Differences in WAZ and HAZ Scores between Left-Behind Children and Children with Parents

Child Anthropometric Measures	Weight-for-Age Z scores (WAZ)				Height-for-Age Z scores (HAZ)			
	Characteristics effect		Coefficients effect		Characteristics effect		Coefficients effect	
	Est.	Share	Est.	Share	Est.	Share	Est.	Share
Aggregate effect	-.083**	39.2	-.129***	60.8	-.367***	62.0	-.225***	38.0
Social disadvantage indicators	-.024***	11.4	.221	-104.3	-.040***	6.8	.184	-31.2
Rural hukou	-.021***	9.7	.208	-98.3	-.016	2.7	.134	-22.7
Female-headed HH	-.004	2.1	.029	-13.9	-.025**	4.2	-.014	2.4
Child is a girl	.001	-0.4	-.017	7.9	.000	-0.1	.064	-10.9
Household level controls	-.060*	28.2	-.363	171.6	-.162***	27.4	.280	-47.3
Occup. rank of HH head	-.012**	5.6	-.121	57.1	.006	-1.0	.108	-18.2
2nd consumption quartile	.004	-1.9	.012	-5.8	-.004	0.7	-.055*	9.3
3rd consumption quartile	-.003	1.4	-.025	11.7	-.008	1.3	-.041	6.9
Top consumption quartile	.016	-7.4	.023	-10.8	-.038**	6.4	-.014	2.4
Food share in consumption	.007	-3.2	-.139	65.6	-.004	0.7	-.262	44.3
Usual hours worked	-.033***	15.4	.035	-16.6	-.004	0.6	-.072	12.1
Mother's years of education	-.049***	23.4	-.129	60.9	-.106***	18.0	-.173	29.2
Father's years of education	-.008	3.9	.121	-57.3	-.008	1.4	.086	-14.5
Age of HH head	.018	-8.5	.096	-45.6	-.002	0.4	.311	-52.5
HH head has Han ethnicity	-.004	1.9	-.270	127.8	-.001	0.2	.500	-84.5
Height of HH head	.005	-2.4	.033	-15.4	.007	-1.2	-.108	18.2
Village controls	.000	-0.2	-.261*	123.4	.006	-1.1	.086	-14.5
City controls	-.017	8.0	-.147	69.3	.016***	-2.8	-3.704	625.6
Year & Region fixed effects	.005	-2.3	.184	-87.2	-.134***	22.6	.008	-1.3
constant			.300	-142.1			2.820	-476.3

Note: Share is the ratio of the contribution of each factor to the overall mean differences in WAZ and HAZ scores between left-behind children and children who live with parents, in percentage terms. The notation *** is p <0.01, ** is p <0.05, * is p <0.10. Total number of observations is 3235, whereas the numbers of observations in group 0 (migrating children live with parents) and in group 1 (left-behind children) are 1429 and 1806, respectively.

Table 6. Selected Detailed Quantile Decomposition of Differences in WAZ Scores between Left-Behind Children and Children with Parents

Quantile (τ)	**.10**				**.20**				**.30**			
	Characteristics effect		Coefficients effect		Characteristics effect		Coefficients effect		Characteristics effect		Coefficients effect	
	Est.	Share	Est.	Share	Est.	Share	Est.	Share	Est.	Share	Est.	Share
Aggregate effect	-.240***	44.7	-.296***	55.3	-.136***	37.5	-.226***	62.5	-.155***	42.3	-.211***	57.7
Social disadvantage indicators	-.033***	6.1	-.130	24.2	-.039***	10.8	-.226	62.3	-.041***	11.2	-.405***	110.8
Household level controls	-.141***	26.4	.443	-82.6	-.061	16.7	2.272	-626.8	-.096***	26.2	.921	-252.2
Village controls	-.001	.2	-.087	16.3	.001	-0.3	-.150	41.4	-.001	.3	-.071	19.3
City controls	.004	-.8	-2.934	547.6	-.002	.4	-3.046	840.3	-.001	.2	-3.204	877.3
Year & Region fixed effects	-.069	12.9	-.148	-27.6	-.036	9.9	.177	-48.8	-.016	4.5	.240	-65.7
constant			2.264	-422.5			.747	-206.0			2.308	-631.9
Quantile (τ)	**.40**				**.50**				**.60**			
Aggregate effect	-.082**	47.7	-.090*	52.3	-.113***	40.2	-.167***	59.8	-.039	58.8	-.027	41.2
Social disadvantage indicators	-.035***	20.4	-.131	76.2	-.037***	13.2	.016	-5.6	-.024**	35.9	-.222	335.9
Household level controls	-.043	25.2	.700	-406.8	-.061	21.9	-1.462	521.8	-.017	25.9	-2.813*	4262.5
Village controls	-.001	0.6	-.145	84.3	-.001	0.4	-.255**	91.2	-.003	4.6	-.282***	427.1
City controls	-.019	11.2	-1.897	1102	-.032	11.5	-.368	131.4	-.029	44.2	.140	-211.8
Year & Region fixed effects	.017	-9.8	.109	-63.6	.019	-6.8	.052	18.6	.034	-51.8	.026	-38.9
constant			1.274	-740.4			1.954	-697.7			3.175	-4811
Quantile (τ)	**.70**				**.80**				**.90**			
Aggregate effect	-.032	58.4	-.023	41.6	-.027	359.8	.020	-259.8	.077	-707.7	-.088	807.7
Social disadvantage indicators	-.013	23.7	-.146	268.2	-.002	25.4	-.768***	10099.3	-.012	112.4	.671	-6140.5
Household level controls	-.059	108.9	-2.851	5249.3	.069	-909.7	.638	-8384.2	-.040	367.4	-2.697	24692.2
Village controls	.001	-1.9	-.253*	466.4	-.004	56.9	.269	-3537.5	-.004	35.4	-.298	2732.4
City controls	-.038	69.6	1.465	-2696	.046	-602	-3.196	42037	.035	-320	6.070	-55570
Year & Region fixed effects	.077*	-142	-.137	252.5	-.136***	1789	.066	863.8	.099	-903	-.154	1414
constant			1.900	-3498			3.012	-39611			-3.679	33679

Note: Share is the ratio of the contribution of each factor to the overall differences in WAZ between left-behind children and children who live with parents, in percentage terms. The notation *** is p <0.01, ** is p <0.05, * is p <0.10.

Table 7. Selected Detailed Quantile Decomposition of Differences in HAZ Scores between Left-Behind Children and Children with Parents

Quantile (τ)	**.10**				**.20**				**.30**			
	Characteristics effect		Coefficients effect		Characteristics effect		Coefficients effect		Characteristics effect		Coefficients effect	
	Est.	Share	Est.	Share	Est.	Share	Est.	Share	Est.	Share	Est.	Share
Aggregate effect	-.521***	92.4	-.043	7.6	-.509***	63.5	-.292***	36.5	-.430***	64.8	-.233***	35.2
Social disadvantage indicators	-.006	1.0	-.770*	136.6	-.052***	6.5	.137	-17.1	-.056***	8.4	.148***	-22.4
Household level controls	-.410***	72.7	-1.994	353.4	-.313***	39.1	-7.375***	920.7	-.257***	38.8	-2.874	433.7
Village controls	.005	-0.8	.234	-41.6	-.002	0.2	-.032	3.9	.006	-0.8	.071	-10.7
City controls	.016	-2.8	-4.792	849.6	.001	-.1	-3.471	433.3	.038	-5.8	-2.809	423.9
Year & Region fixed effects	-.125	22.2	.340	-60.3	-.143***	17.8	.316	-39.5	-.161***	24.3	.194	-29.2
constant			6.939	-1230			10.132	-1265			5.037	-760.1
Quantile (τ)	**.40**				**.50**				**.60**			
Aggregate effect	-.470***	60.8	-.303***	39.2	-.394***	67.8	-.188***	32.2	-.318***	57.0	-.240***	43.0
Social disadvantage indicators	-.054***	7.0	.581	-75.2	-.044***	7.5	.273	-47.0	-.043***	7.7	.456	-81.7
Household level controls	-.257***	33.3	-2.347	303.8	-.211***	36.2	2.444	-420.3	-.160***	28.6	4.069***	-729.0
Village controls	.009	-1.2	.070	-9.0	.010	-1.6	-.025	4.3	.010	-1.8	-.081	14.5
City controls	.010	-1.3	-3.939	509.8	.020	-3.5	-3.334	573.2	-.011	1.9	-2.645	473.9
Year & Region fixed effects	-.178***	23.1	-.008	1.1	-.017***	29.2	-.075	12.9	-.114***	20.5	.028	-4.4
constant			5.341	-691.3			.529	-91.0			-2.064	369.8
Quantile (τ)	**.70**				**.80**				**.90**			
Aggregate effect	-.297***	54.0	-.252***	46.0	-.225***	66.4	-.114	33.6	-.245***	66.7	-.122	33.3
Social disadvantage indicators	-.051***	9.2	-.030	5.5	-.043***	12.6	.601	-177.3	-.048*	13.1	.118	-32.3
Household level controls	-.141***	25.6	4.009***	-730.5	-.080	23.5	4.025***	-1187.0	-.137***	37.3	.484	-132.0
Village controls	.008	-1.5	.010	-1.8	.002	-0.7	.190	-56.0	.008	-2.2	-.112	30.6
City controls	.014	-2.6	-1.582	288.3	.013	-3.8	-1.602	472.5	.018	-4.9	-1.887	514.9
Year & Region fixed effects	-.127***	23.2	-.027	4.9	-.118***	34.8	-.339	99.9	-.086	23.4	-.331	90.3
constant			-2.632	479.5			-2.990	881.6			1.606	-438.3

Note: Share is the ratio of the contribution of each factor to the overall differences in WAZ between left-behind children and children who live with parents, in percentage terms. The notation *** is p <0.01, ** is p <0.05, * is p <0.10.

Table 8. Quantile Treatment Effects of Counterfactual Distribution Estimations and Inferences

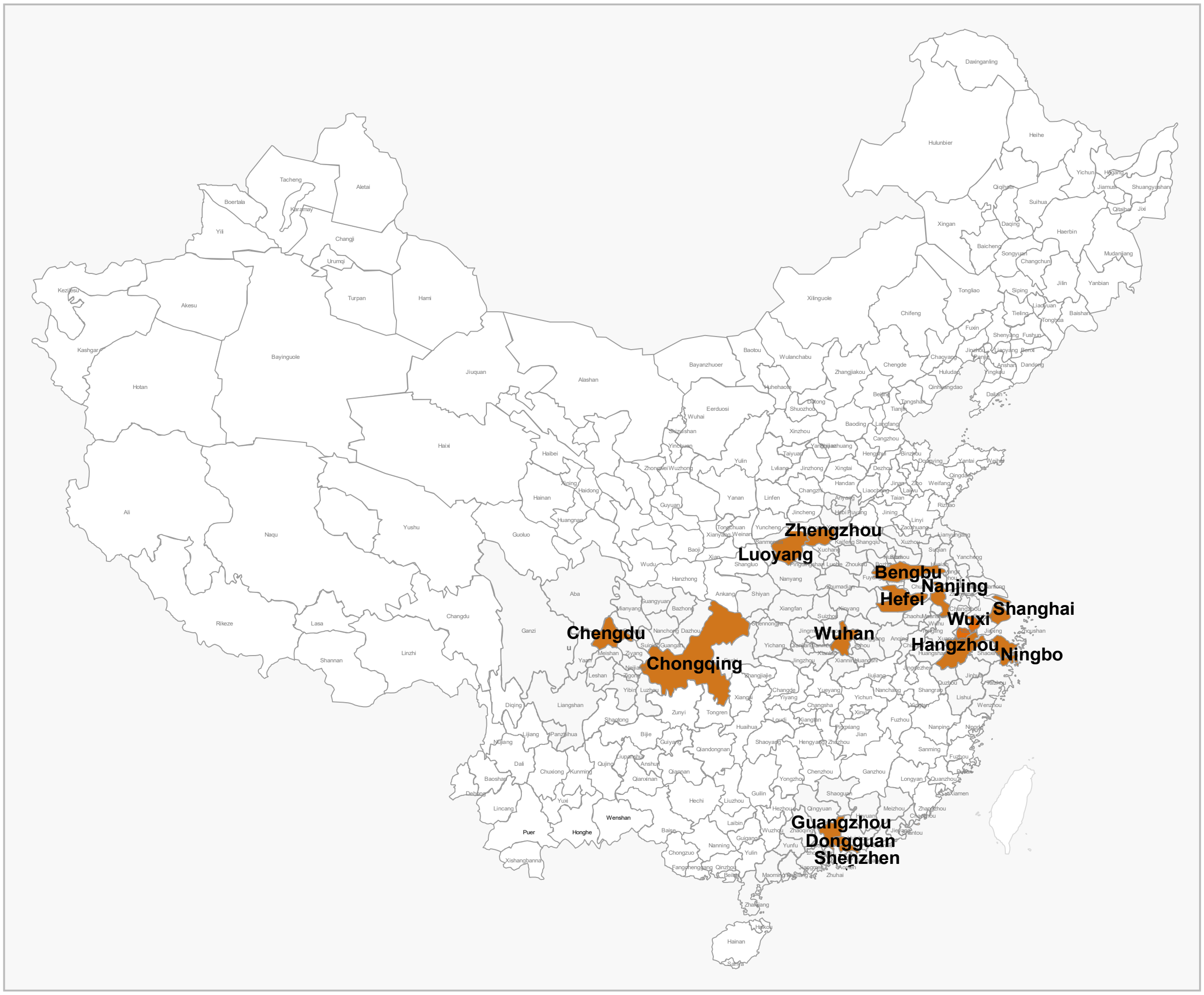
	Weight-for-Age Z scores (WAZ)		Height-for-Age Z scores (HAZ)	
Quantile (τ)	Quantile Treatment Effect (QTE)	Pointwise Standard error	Quantile Treatment Effect (QTE)	Pointwise Standard error
.10	.163***	.065	.414***	.108
.20	.102***	.057	.454***	.101
.30	.066	.051	.376***	.078
.40	.041	.050	.331***	.068
.50	.028	.050	.281***	.066
.60	.023	.052	.222***	.069
.70	.005	.057	.169***	.074
.80	-.016	.066	.203***	.079
.90	-.062	.077	.198***	.077

Bootstrap inference on the counterfactual quantile processes

	P-values (WAZ)		P-values (HAZ)	
Null hypothesis	Kolmogorov-Smirnov statistics	Cramer-von-Misses-Smirnov statistic	Kolmogorov-Smirnov statistics	Cramer-von-Misses-Smirnov statistic
(1) Correct specification of the parametric model	1.000	1.000	1.000	1.000
(2) No effect: QTE(τ)=0 for all τ	.066	.214	.000	.000
(3) Constant effect: QTE(τ)=QTE(.5) for all τ	.182	.162	.084	.038
(4) Stochastic dominance: QTE(τ)>0 for all τ	.470	.744	.870	.870
(5) Stochastic dominance: QTE(τ)<0 for all τ	.034	.116	.000	.000

Note: Bootstrapped standard errors in parenthesis. The variance has been estimated by bootstrapping the results 500 times. The conditional model is estimated by linear quantile regressions with 300 times. The total number of observations is 3235, whereas the numbers of observations in the reference group (migrating children who live with parents) and in the counterfactual group (left-behind children) are 1429 and 1806, respectively. The notation *** is $p < 0.01$.

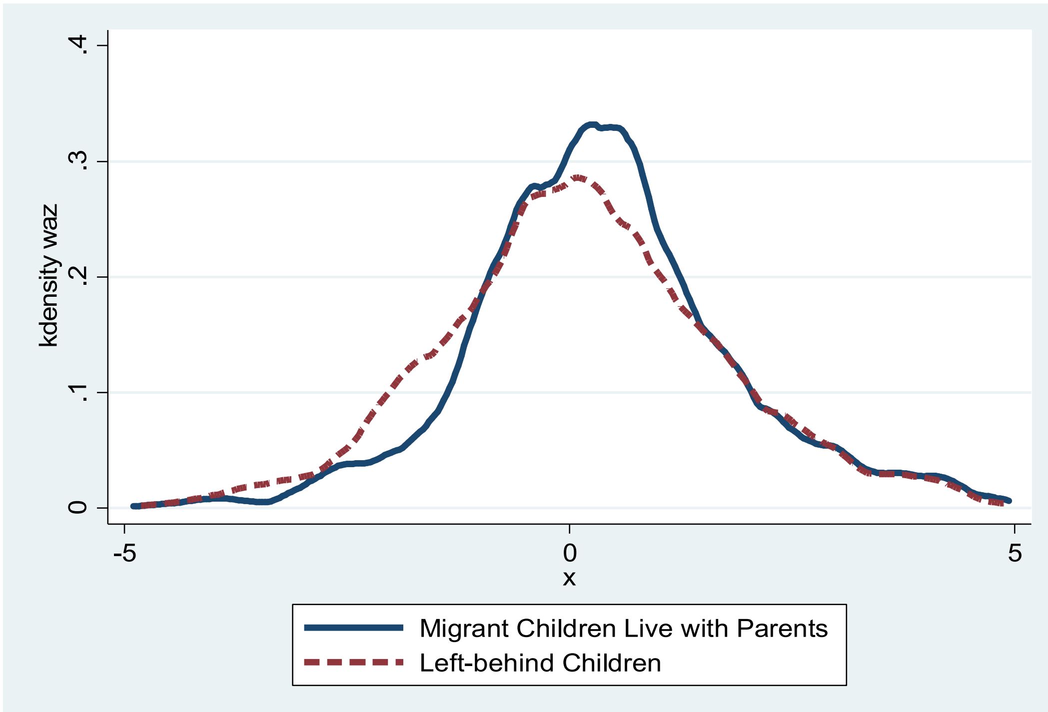
Figure 1. Spatial Coverage of the Urban Migrant Survey in RUMiC data



Note: The survey covers 15 cities as indicated by the dark areas on the map − Bengbu, Chengdu, Chongqing, Dongguan, Guangzhou, Hefei, Hangzhou, Luoyang, Nanjing, Ningbo, Shanghai, Shenzhen, Wuhan, Wuxi, and, Zhengzhou. They are either provincial capital cities or other major migrant receiving cities.

Figure 2. Kernel Density Estimates of Child Anthropometric Measures

Panel A: Weight-for-Age Z-Scores



Panel B: Height for Age Z-Scores

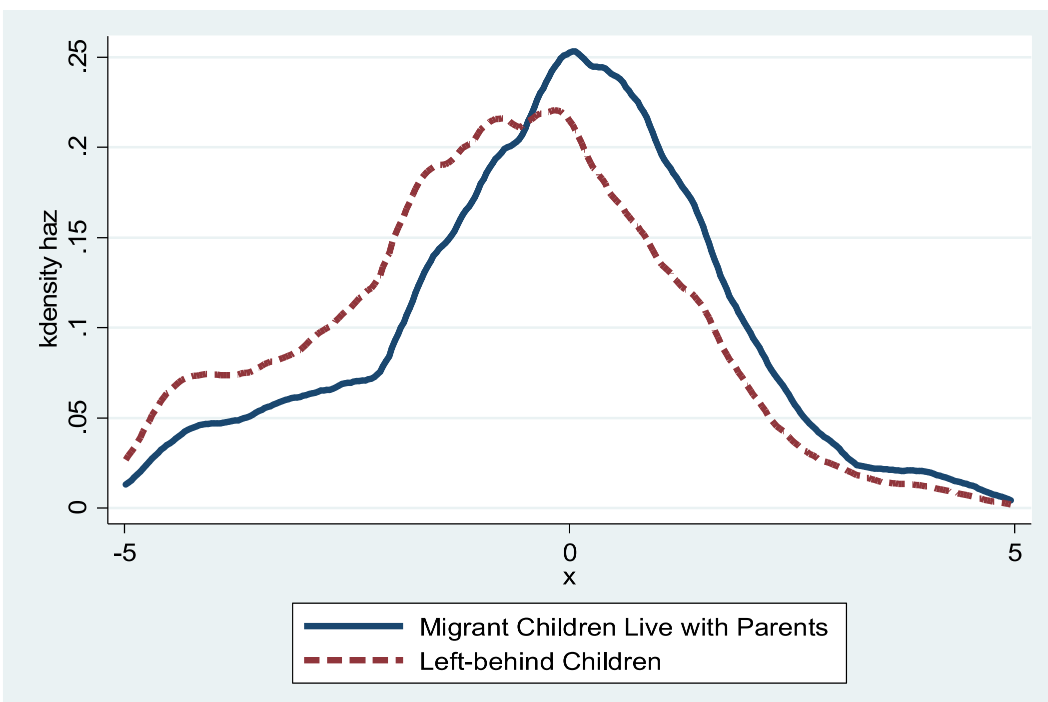


Figure 3. Quantile Decomposition Results for WAZ-Score Gaps between Left-Behind Children and Children Who Live with Their Parents

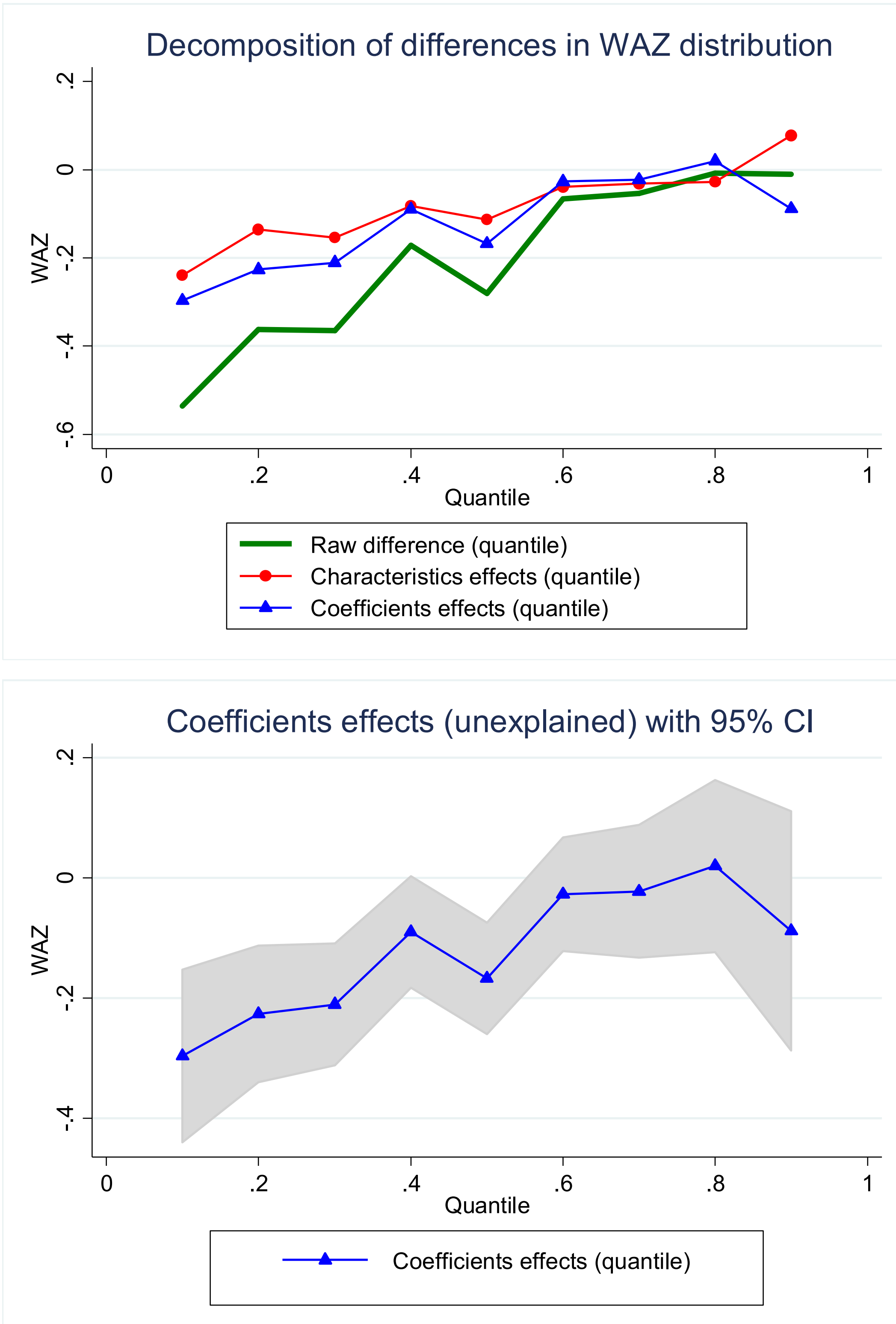


Figure 4. Quantile Decomposition Results for HAZ-Score Gaps between Left-Behind Children and Children Who Live with Their Parents

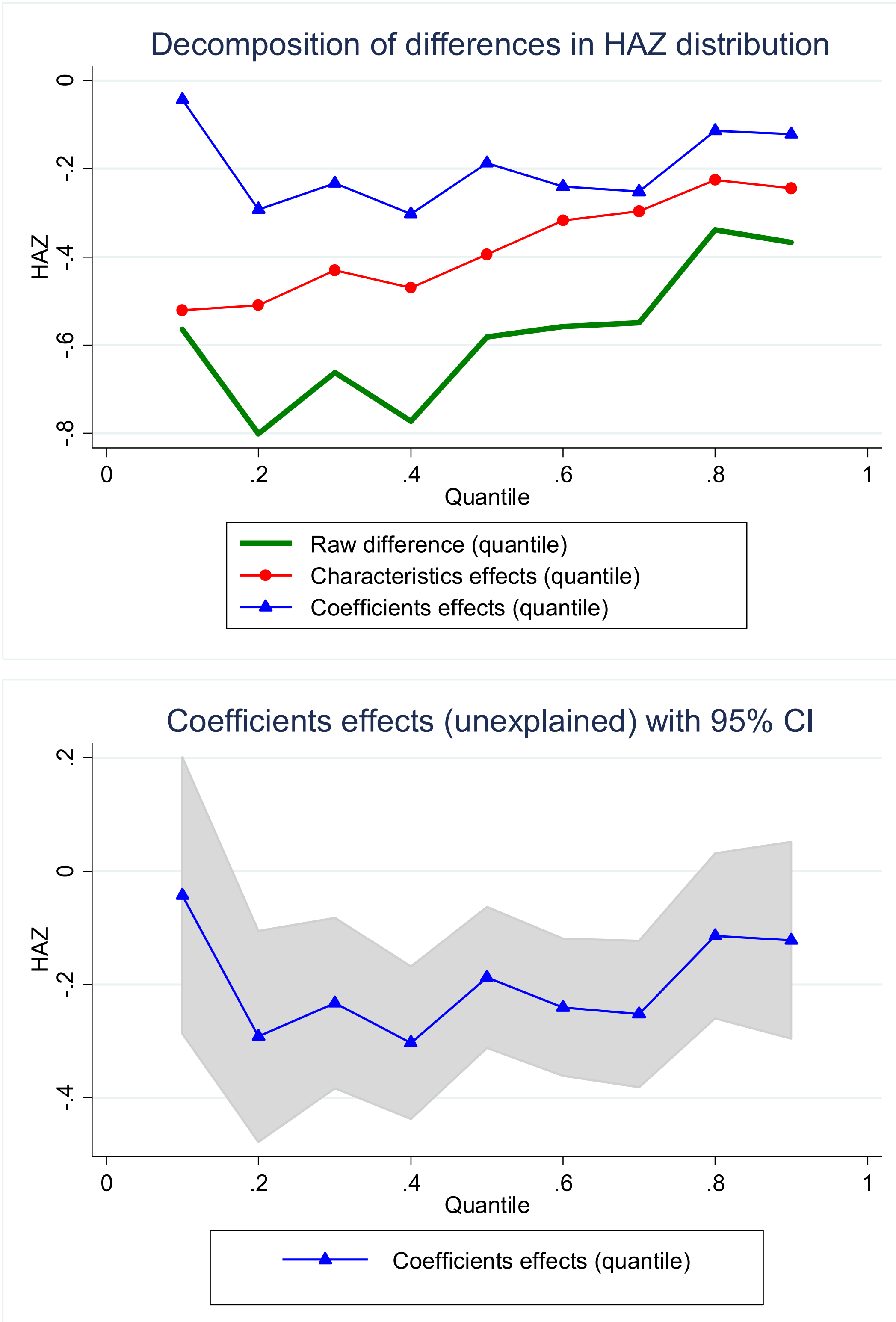
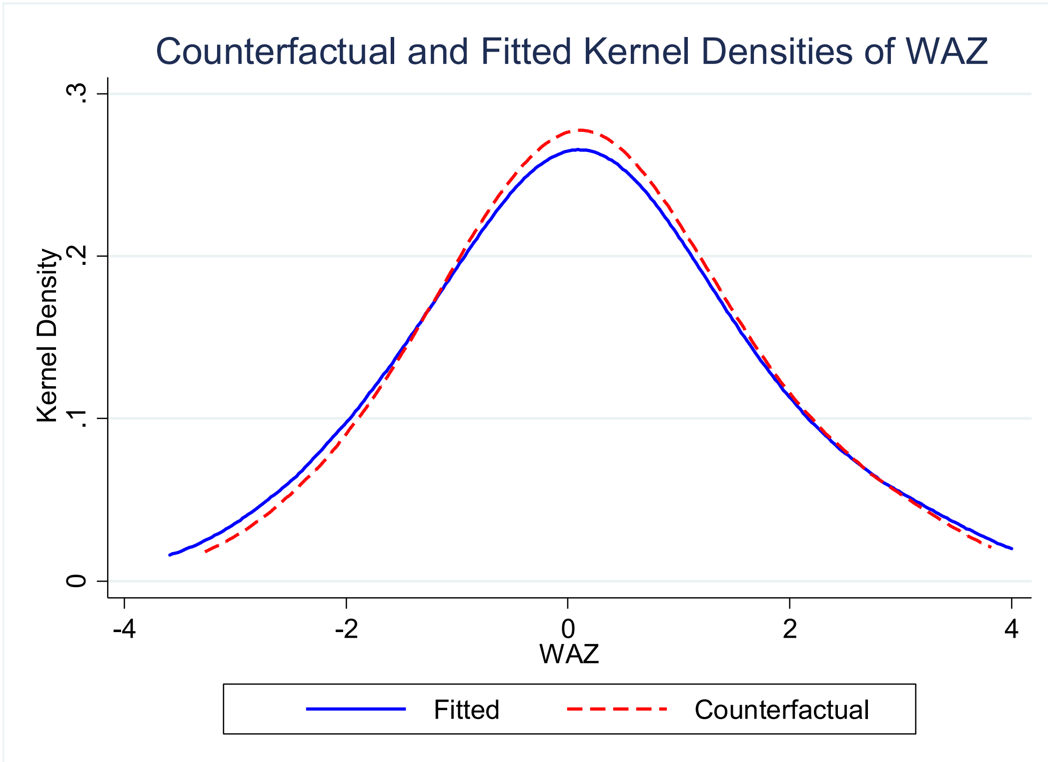


Figure 5. Counterfactual Quantile Treatment Effects for WAZ Scores



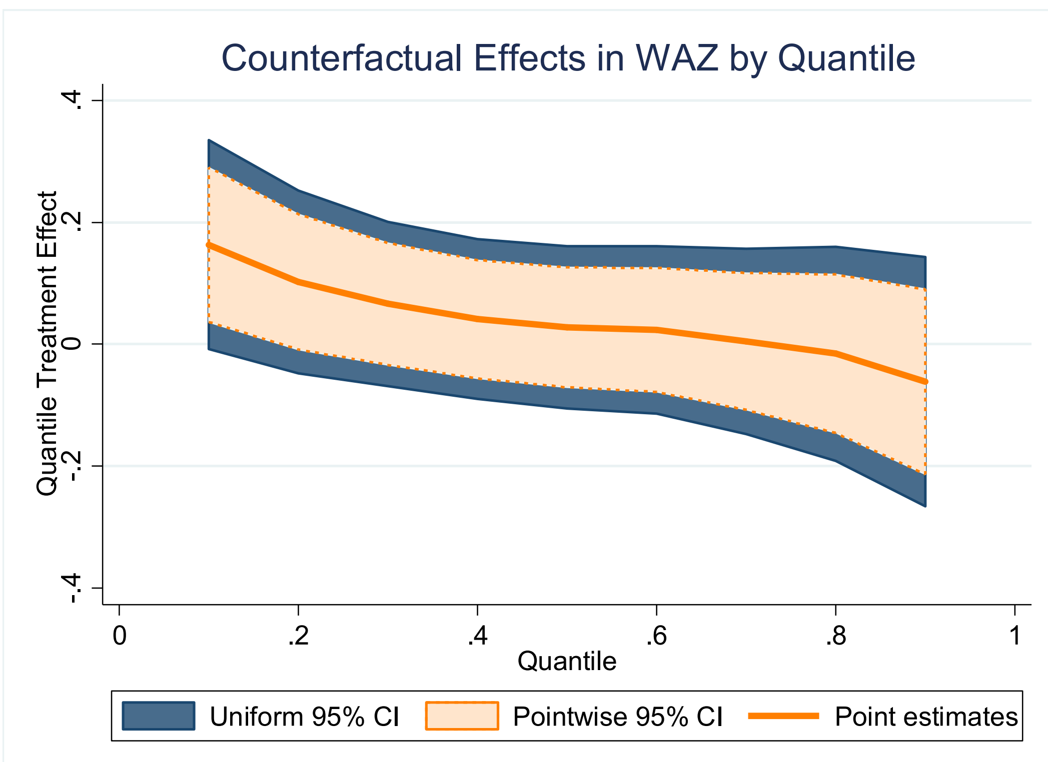
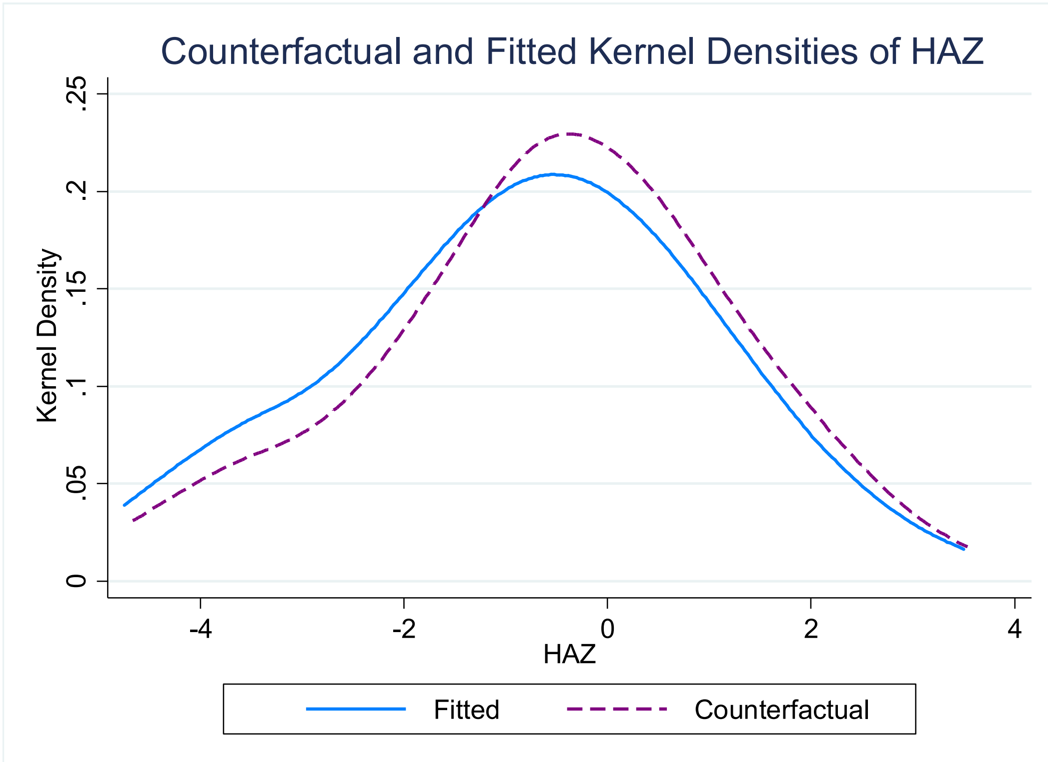
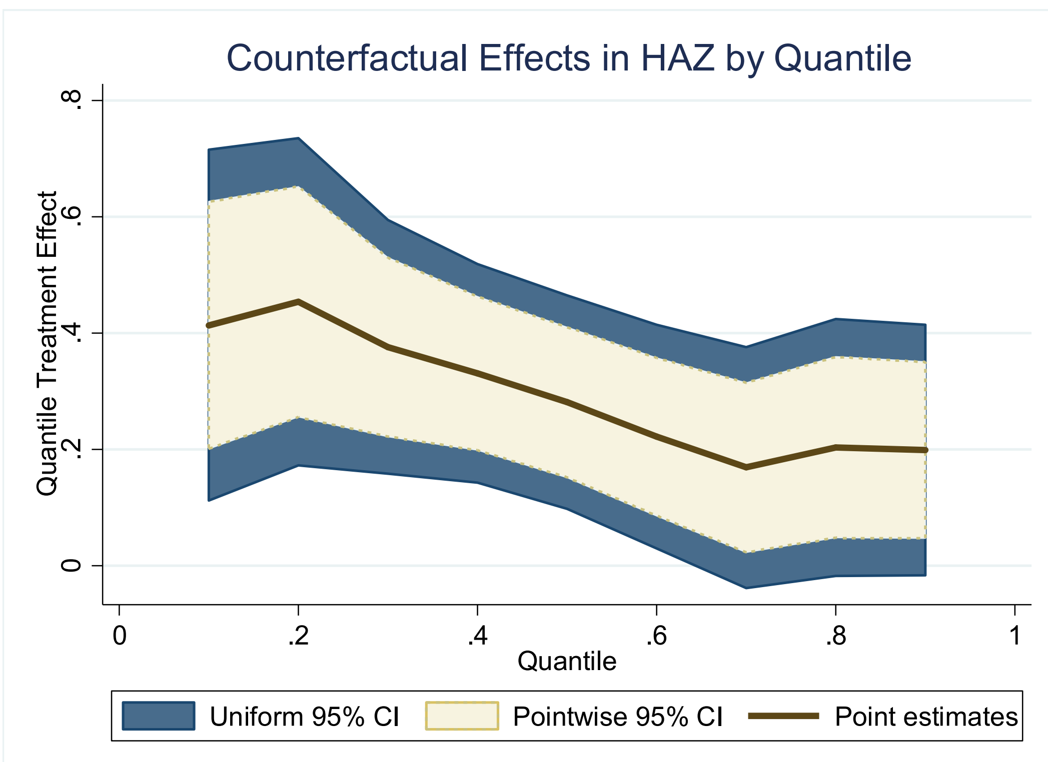


Figure 6. Counterfactual Quantile Treatment Effects for HAZ Scores





Appendix Table 1. Full Detailed Quantile Decomposition of Differences in WAZ Distributions between Left-Behind Children and Children with Parents

Quantile (τ)	.10				.20				.30			
	Characteristics effect		Coefficients effect		Characteristics effect		Coefficients effect		Characteristics effect		Coefficients effect	
	Est.	Share	Est.	Share	Est.	Share	Est.	Share	Est.	Share	Est.	Share
Aggregate effect	-.240***	44.7	-.296***	55.3	-.136***	37.5	-.226***	62.5	-.155***	42.3	-.211***	57.7
Social disadvantage indicators	-.033***	6.1	-.130	24.2	-.039***	10.8	-.226	62.3	-.041***	11.2	-.405***	110.8
Rural hukou	-.026**	4.8	-.129	24.1	-.030***	8.3	-.300	82.8	-.031***	8.4	-.518***	141.7
Female-headed HH	-.007	1.4	.045	-8.5	-.010	2.7	.039	-10.7	-.011*	3.0	.033	-9.1
Child is a girl	.000	-.1	-.046	8.5	.000	-0.1	.035	-9.8	.001	-0.2	.080**	-21.8
Household level controls	-.141***	26.4	.443	-82.6	-.061	16.7	2.272	-626.8	-.096***	26.2	.921	-252.2
Occup. rank of HH head	-.003	.6	.021	-3.9	-.008	2.3	-.013	3.5	-.007	2.0	-.052	14.3
2nd consumption quartile	.000	-.1	-.057	10.7	-.008	2.2	-.042	11.5	.005	-1.4	-.024	6.6
3rd consumption quartile	.003	-.6	-.086	16.0	.014	-3.9	-.087	23.9	-.006	1.7	-.079	21.7
Top consumption quartile	-.017	3.2	-.052	9.6	.052	-14.4	-.034	9.5	.010	-2.6	-.018	5.0
Food share in consumption	-.007	1.3	.021	-4.0	-.005	1.2	.073	-20.1	.008	-2.3	-.002	0.5
Usual hours worked	-.013	2.5	.128	-23.9	-.036	10.0	-.014	3.9	-.035**	9.5	.062	-16.9
Mother’s years of education	-.115***	21.5	.016	-3.0	-.073***	20.1	.014	-4.0	-.069***	18.9	-.089	24.2
Father’s years of education	.007	-1.3	-.192	35.8	-.008	2.2	-.022	6.0	-.019*	5.1	.014	-3.8
Age of HH head	.005	-.9	.867**	-161.7	.008	-2.3	.171	-47.3	.013	-3.5	-.066	18.0
HH head has Han ethnicity	-.006	1.2	.193	-36.0	-.004	1.2	-.012	3.2	-.004	1.0	-.228	62.6
Height of HH head	.005	-1.0	-.417	77.8	.007	-1.9	2.236	-617.0	.008	-2.1	1.404	-384.4
Village controls	-.001	.2	-.087	16.3	.001	-0.3	-.150	41.4	-.001	.3	-.071	19.3
City controls	.004	-.8	-2.934	547.6	-.002	.4	-3.046	840.3	-.001	.2	-3.204	877.3
Year & Region fixed effects	-.069	12.9	-.148	-27.6	-.036	9.9	.177	-48.8	-.016	4.5	.240	-65.7
constant			2.264	-422.5			.747	-206.0			2.308	-631.9
Quantile (τ)	.40				.50				.60			
Aggregate effect	-.082**	47.7	-.090*	52.3	-.113***	40.2	-.167***	59.8	-.039	58.8	-.027	41.2
Social disadvantage indicators	-.035***	20.4	-.131	76.2	-.037***	13.2	.016	-5.6	-.024**	35.9	-.222	335.9
Rural hukou	-.029***	16.9	-.199	115.7	-.033***	11.6	-.048	17.0	-.022	32.6	-.132	200.0
Female-headed HH	-.007	4.3	.042	-24.5	-.005	2.0	.014	-5.0	-.003	4.5	-.027	41.2
Child is a girl	.001	-0.7	.026	-15.0	.001	-0.4	.049	-17.6	.001	-1.2	-.063*	94.8
Household level controls	-.043	25.2	.700	-406.8	-.061	21.9	-1.462	521.8	-.017	25.9	-2.813*	4262.5
Occup. rank of HH head	-.010	6.0	-.101	58.8	-.004	1.3	-.079	28.4	-.008	12.7	-.052	79.5
2nd consumption quartile	-.004	2.1	-.023	13.2	.008	-2.7	.011	-3.8	.006	-8.7	.007	-10.6

3rd consumption quartile	.003	-1.7	-.061	35.7	-.007	2.5	-.021	7.5	-.005	7.6	-.006	8.6
Top consumption quartile	.039	-22.9	-.011	6.2	-.001	0.5	.014	-5.1	.016	-23.8	.014	-21.8
Food share in consumption	.013	-7.7	-.080	46.5	.005	-1.7	-.171*	61.2	.005	-7.4	-.138	208.6
Usual hours worked	-.035**	20.2	.037	-21.6	-.034**	12.0	-.017	6.1	-.026**	39.9	.030	-46.1
Mother's years of education	-.062***	36.1	-.081	46.8	-.038**	13.7	-.116	41.3	-.020	30.7	-.103	155.6
Father's years of education	-.008	4.7	.060	-35.0	-.011	3.8	.192*	-68.5	-.006	9.5	.137	-207.4
Age of HH head	.016	-9.4	-.073	42.2	.018	-6.3	-.579**	206.7	.021	-31.8	-.974***	1476.2
HH head has Han ethnicity	-.003	1.7	-.274	159.2	-.003	0.9	-.378	134.9	-.003	5.1	-.231	350.6
Height of HH head	.007	-3.8	1.306	-758.9	.006	-2.1	-.317	113.1	.005	-7.8	-1.498	2269.2
Village controls	-.001	0.6	-.145	84.3	-.001	0.4	-.255**	91.2	-.003	4.6	-.282***	427.1
City controls	-.019	11.2	-1.897	1102	-.032	11.5	-.368	131.4	-.029	44.2	.140	-211.8
Year & Region fixed effects	.017	-9.8	.109	-63.6	.019	-6.8	.052	18.6	.034	-51.8	.026	-38.9
constant			1.274	-740.4			1.954	-697.7			3.175	-4811
Quantile (τ)	.70				.80				.90			
Aggregate effect	-.032	58.4	-.023	41.6	-.027	359.8	.020	-259.8	.077	-707.7	-.088	807.7
Social disadvantage indicators	-.013	23.7	-.146	268.2	-.002	25.4	-.768***	10099.3	-.012	112.4	.671	-6140.5
Rural hukou	-.012	22.2	-.020	36.3	-.004	58.1	-.800**	10517.8	-.006	54.9	.689	-6305.9
Female-headed HH	-.002	3.7	-.053	96.7	.004	-57.6	-.039	517.9	-.009	78.4	.035	-320.7
Child is a girl	.001	-2.2	-.073*	135.2	-.002	24.8	.071	-936.3	.002	-21.0	-.053	486.1
Household level controls	-.059	108.9	-2.851	5249.3	.069	-909.7	.638	-8384.2	-.040	367.4	-2.697	24692.2
Occup. rank of HH head	-.010	17.6	-.099	182.6	.022**	-290.2	.161	-2119.0	-.037***	341.5	-.355	3246.8
2nd consumption quartile	.008	-14.9	.027	-49.7	-.021**	276.8	-.078	1024.6	.027*	-248.4	.152	-1390.8
3rd consumption quartile	-.008	14.3	.002	-4.6	.01**	-246.1	-.020	259.8	-.017	158.9	.102	-929.9
Top consumption quartile	.002	-3.8	.051	-94.8	.003	-40.6	-.082	1073.6	-.009	81.5	.142	-1296.6
Food share in consumption	.007	-13.6	-.149	274.8	-.009	119.3	.115	-1506.7	.016	-143.7	-.098	894.2
Usual hours worked	-.043*	78.4	-.047	86.9	.051**	-677.2	-.042	549.7	-.051**	465.0	-.081	740.8
Mother's years of education	-.026	47.9	-.069	126.9	.025	-332.5	.191	-2507.3	.005	-42.6	-.277	2535.4
Father's years of education	-.015	27.8	.160	-294.7	.006	-83.1	-.270	3545.2	-.006	56.4	.180	-1651.1
Age of HH head	.024	-44.4	-.593*	1092.5	-.030	399.0	.149	-1961.1	.030	-272.3	.330	-3017.1
HH head has Han ethnicity	-.003	6.4	-.310	571.7	.007	-90.3	.386	-5078.2	-.003	28.1	-.212	1938.6
Height of HH head	.004	-6.9	-1.824	3357.7	-.004	55.4	.127	-1664.9	.006	-56.9	-2.580	23621.9
Village controls	.001	-1.9	-.253*	466.4	-.004	56.9	.269	-3537.5	-.004	35.4	-.298	2732.4
City controls	-.038	69.6	1.465	-2696	.046	-602	-3.196	42037	.035	-320	6.070	-55570
Year & Region fixed effects	.077*	-142	-.137	252.5	-.136***	1789	.066	863.8	.099	-903	-.154	1414
constant			1.900	-3498			3.012	-39611			-3.679	33679

Note: Share is the ratio of the contribution of each factor to the overall differences in WAZ between left-behind children and children who live with parents, in percentage terms. The notation *** is $p < 0.01$, ** is $p < 0.05$, * is $p < 0.10$.

Appendix Table 2. Full Detailed Quantile Decomposition of Differences in HAZ Distributions between Left-Behind Children and Children with Parents

Quantile (τ)	.10				.20				.30			
	Characteristics effect		Coefficients effect		Characteristics effect		Coefficients effect		Characteristics effect		Coefficients effect	
	Est.	Share	Est.	Share	Est.	Share	Est.	Share	Est.	Share	Est.	Share
Aggregate effect	-.521***	92.4	-.043	7.6	-.509***	63.5	-.292***	36.5	-.430***	64.8	-.233***	35.2
Social disadvantage indicators	-.006	1.0	-.770*	136.6	-.052***	6.5	.137	-17.1	-.056***	8.4	.148***	-22.4
Rural hukou	.005	-1.0	-.724*	128.4	-.017	2.2	.193	-24.2	-.029**	4.4	.099	-14.9
Female-headed HH	-.011	1.9	-.057	10.2	-.034**	4.2	-.178**	22.2	-.026**	3.9	-.078	11.8
Child is a girl	.000	0.0	.011	-2.0	.000	0.1	.121*	-15.1	-.001	0.1	.127**	-19.2
Household level controls	-.410***	72.7	-1.994	353.4	-.313***	39.1	-7.375***	920.7	-.257***	38.8	-2.874	433.7
Occup. rank of HH head	.037**	-6.5	.292	-51.7	.017	-2.2	.204	-25.4	.002	-0.3	.145	-21.8
2nd consumption quartile	.027	-4.8	-.404**	71.6	.016	-2.0	-.297***	37.1	.006	-1.0	-.178**	26.8
3rd consumption quartile	-.038*	6.8	-.445**	79.0	-.022	2.7	-.267**	33.4	-.012	1.8	-.161	24.3
Top consumption quartile	-.249***	44.1	-.461**	81.8	-.150***	18.8	-.316***	39.4	-.090**	13.6	-.185**	28.0
Food share in consumption	-.012	2.2	-.365	64.7	-.025	3.1	-.028	3.5	-.008	1.2	-.074	11.2
Usual hours worked	-.010	1.7	-.022	3.9	-.002	0.3	.019	-2.4	-.007	1.1	.051	-7.6
Mother's years of education	-.154***	27.4	-.274	48.6	-.122***	15.3	-.104	13.0	-.133***	20.1	-.179	27.0
Father's years of education	.017	-3.0	.010	-1.8	-.015	1.8	-.284	35.5	-.010	1.6	-.027	4.0
Age of HH head	-.022	3.9	-1.012	179.4	-.012	1.5	-.537	67.1	-.008	1.1	.276	-41.7
HH head has Han ethnicity	-.004	0.7	1.406**	-249.2	-.003	0.4	.712	-88.9	-.003	0.4	.722	-109.0
Height of HH head	-.002	0.4	-.718	127.3	.004	-0.6	-6.476**	808.4	.007	-1.0	-3.264	492.6
Village controls	.005	-0.8	.234	-41.6	-.002	0.2	-.032	3.9	.006	-0.8	.071	-10.7
City controls	.016	-2.8	-4.792	849.6	.001	-.1	-3.471	433.3	.038	-5.8	-2.809	423.9
Year &Region fixed effects	-.125	22.2	.340	-60.3	-.143***	17.8	.316	-39.5	-.161***	24.3	.194	-29.2
constant			6.939	-1230			10.132	-1265			5.037	-760.1
Quantile (τ)	.40				.50				.60			
Aggregate effect	-.470***	60.8	-.303***	39.2	-.394***	67.8	-.188***	32.2	-.318***	57.0	-.240***	43.0
Social disadvantage indicators	-.054***	7.0	.581	-75.2	-.044***	7.5	.273	-47.0	-.043***	7.7	.456	-81.7
Rural hukou	-.032**	4.2	.595	-77.0	-.015	2.6	.140	-24.0	-.014	2.5	.307	-55.0
Female-headed HH	-.022**	2.9	-.061	7.9	-.029**	5.0	.066	-11.3	-.029***	5.2	.068	-12.2
Child is a girl	.000	-0.1	.047	-6.1	.001	-0.2	.067	-11.6	.000	0.0	.082*	-14.6
Household level controls	-.257***	33.3	-2.347	303.8	-.211***	36.2	2.444	-420.3	-.160***	28.6	4.069***	-729.0
Occup. rank of HH head	.004	-0.5	-.013	1.7	-.002	0.3	.005	-0.9	-.001	0.2	.117	-21.0
2nd consumption quartile	.006	-0.8	-.140**	18.1	.010	-1.6	-.091	15.6	.010	-1.7	-.080	14.4

3rd consumption quartile	-.015	1.9	-.130	16.9	-.017	2.8	-.064	10.9	-.014	2.5	-.089	16.0
Top consumption quartile	-.092**	11.9	-.101	13.0	-.092**	15.8	-.027	4.6	-.053	9.5	-.007	1.2
Food share in consumption	-.011	1.4	-.128	16.6	.008	-1.3	-.075	13.0	-.004	0.7	-.133	23.9
Usual hours worked	.000	0.0	.014	-1.8	-.008	1.4	-.139	23.9	-.011	1.9	-.053	9.5
Mother's years of education	-.134***	17.4	-.053	6.8	-.111***	19.1	-.143	24.6	-.073***	13.1	-.116	20.8
Father's years of education	-.014	1.9	.047	-6.1	-.006	0.9	.204	-35.1	-.022*	4.0	.135	-24.2
Age of HH head	-.006	0.8	1.084***	-140.4	-.004	0.7	1.183***	-203.3	-.001	0.2	1.266***	-226.8
HH head has Han ethnicity	.000	0.0	.794**	-102.7	.001	-0.2	.618*	-106.3	.000	-0.1	.493	-88.4
Height of HH head	.006	-0.8	-3.721*	481.6	.010	-1.6	.972	-167.1	.010	-1.7	2.536	-454.4
Village controls	.009	-1.2	.070	-9.0	.010	-1.6	-.025	4.3	.010	-1.8	-.081	14.5
City controls	.010	-1.3	-3.939	509.8	.020	-3.5	-3.334	573.2	-.011	1.9	-2.645	473.9
Year & Region fixed effects	-.178***	23.1	-.008	1.1	-.017***	29.2	-.075	12.9	-.114***	20.5	.028	-4.4
constant			5.341	-691.3			.529	-91.0			-2.064	369.8
Quantile (τ)		.70				.80				.90		
Aggregate effect	-.297***	54.0	-.252***	46.0	-.225***	66.4	-.114	33.6	-.245***	66.7	-.122	33.3
Social disadvantage indicators	-.051***	9.2	-.030	5.5	-.043***	12.6	.601	-177.3	-.048*	13.1	.118	-32.3
Rural hukou	-.025*	4.5	-.191	34.8	-.017	5.0	.511	-150.7	-.028	7.7	.156	-42.6
Female-headed HH	-.027**	4.9	.109*	-19.9	-.027*	8.1	.149**	-44.0	-.021*	5.8	-.016	4.3
Child is a girl	.001	-0.2	.052	-9.5	.001	-0.4	-.059	17.5	.002	-0.4	-.022	6.1
Household level controls	-.141***	25.6	4.009***	-730.5	-.080	23.5	4.025***	-1187.0	-.137***	37.3	.484	-132.0
Occup. rank of HH head	.001	-0.3	.087	-15.9	-.002	0.7	.076	-22.4	-.004	1.1	.028	-7.8
2nd consumption quartile	.002	-0.3	-.047	8.5	-.005	1.6	-.039	11.5	.001	-0.2	.039	-10.8
3rd consumption quartile	-.018*	3.3	-.094	17.2	-.021*	6.2	-.074	21.9	-.030**	8.3	.070	-19.2
Top consumption quartile	-.043	7.8	-.018	3.2	.001	-0.3	.023	-6.7	-.037	10.1	.157	-42.8
Food share in consumption	-.001	0.1	-.173	31.5	-.016	4.7	-.319**	94.0	.007	-1.8	-.278	75.9
Usual hours worked	-.008	1.4	-.127	23.2	.001	-0.3	-.306**	90.2	.000	-0.1	-.240	65.5
Mother's years of education	-.068***	12.4	-.239**	43.5	-.041	12.1	-.218*	64.4	-.095***	26.0	-.138	37.8
Father's years of education	-.023*	4.3	.252	-46.0	-.022	6.4	.344*	-101.5	.006	-1.6	.069	-18.7
Age of HH head	.006	-1.1	.531	-96.8	.013	-3.8	-.126	37.3	.010	-2.6	-.376	102.7
HH head has Han ethnicity	.000	0.0	.217	-39.5	.003	-0.8	-.062	18.2	-.002	0.5	-.442	120.5
Height of HH head	.011	-2.1	3.619*	-659.4	.011	-3.2	4.727**	-1393.8	.009	-2.3	1.595	-435.2
Village controls	.008	-1.5	.010	-1.8	.002	-0.7	.190	-56.0	.008	-2.2	-.112	30.6
City controls	.014	-2.6	-1.582	288.3	.013	-3.8	-1.602	472.5	.018	-4.9	-1.887	514.9
Year & Region fixed effects	-.127***	23.2	-.027	4.9	-.118***	34.8	-.339	99.9	-.086	23.4	-.331	90.3
constant			-2.632	479.5			-2.990	881.6			1.606	-438.3

Note: Share is the ratio of the contribution of each factor to the overall differences in WAZ between left-behind children and children who live with parents, in percentage terms. The notation *** is p <0.01, ** is p <0.05, * is p <0.10.

ENDNOTES

1 See Alderman *et al.* (2006) and Currie (2009) for reviews of the literature on the long-term effects of children's health.

2 For evidence on the relationship between household socioeconomic status and child health, see, for example, Bhattacharya *et al.* (2004), Chowa *et al.* (2010), Currie and Lin (2007), and Rodgers (2011).

3 These studies include Gustafsson and Li (2000), Dong and Bowles (2002), Chi and Li (2014), and Xiu and Gunderson (2015).

4 Data collection was supported by the Institute for the Study of Labor, which provides the Scientific Use Files through its data center. More information about the data can be found in Akgüç *et al*. (2014) and Fang *et al.* (2016).

5 We conducted a series of robustness checks with children ages 0-12 and found the results to be qualitatively consistent.

6 In the RUMiC surveys, we are able to distinguish between migrating children who live with parents in the household and those who are left behind from the questions "Where is the current primary residential place of the child located?" and "Where did the child reside in 2007 (or 2008)?"

7 Further details regarding the listing scheme and random sampling procedures of the survey can be found in Gong *et al.* (2008) and Kong (2010).

8 Note that the survey asks parents the current height and weight of a child. This recall method, which is used largely because many children in the sample do not live with their parents, is less accurate than using scales. However, surveyors are affiliated with the National Bureau of Statistics of China and are highly experienced, which could help to minimize measurement error.

9 A very small proportion of left-behind children in rural hometowns have an urban hukou, which is possible if their parents had been able to successfully acquire an urban hukou and if some unforeseen event (such as a family emergency or sickness) caused the parents to send their child back to the rural hometown.

10 City level characteristics are measured with data from the National Bureau of Statistics of China (various years).

11 We also ran models with fixed effects at the province level and the results are very similar.

12 A related issue that has received attention in the literature is that the detailed decomposition is not invariant to the choice of the reference category when sets of dummy variables are used (Oaxaca and Ransom, 1999; Horrace and Oaxaca, 2001; Gardeazabal and Ugidos, 2004; Yun,

2005; Jann, 2008). If a model includes dummy variables, then the sum of the detailed coefficient effects attributed to the dummy variables is not invariant to the choice of the reference or the omitted category (Powers, Yoshioka, and Yun, 2011). Because we have several categorical variables in the regression, we apply the solution proposed by Gardeazabal and Ugidos (2004) and Yun (2005) and implement the method in Jann (2008).

13 While Fortin *et al*. (2011) use a local inversion procedure to translate a decomposition of a probability gap into a quantile gap, Chernozhukov *et al*. (2013) use a more complicated global inversion procedure. We performed both methods and found that the results are very similar. In section IV, we only report results based on the Fortin *et al*. (2011) method because RIF-regressions have the advantage of being directly comparable to conventional Oaxaca decompositions.

14 Chernozhukov *et al*. (2013) suggest using quantile regressions to estimate these conditional distributions when the dependent variable is continuous as in our case. Our study reports the results for running the quantile regressions 300 times, but we also ran them 100 (minimum suggested) and 200 times to approximate the conditional distributions and found the results to be very similar.

15 The few empirical studies that have examined China's ethnic minorities have mostly focused on rural areas because that is where most ethnic minority groups live (Gustafsson and Li 2003; Zhang 2008; Gustafsson and Ding 2009a and 2009b; and Wu and Song 2014). Hence very little is known regarding how China's ethnic minorities have fared in urban areas. Regarding health inequities by ethnicity, Ouyang and Pinstrup-Andersen (2012) used the China Health and Nutrition Survey from 1989 to 2006 and found negative effects for being an ethnic minority compared to Han Chinese in a set of anthropometric measures for people of all age groups. These results are based on non-migrant households.