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ABSTRACT

Parental Migration Decisions and Child Health Outcomes: Evidence from China*

This study uses migrant household survey data from 2008 and 2009 to examine how parental migration decisions are associated with the nutritional status of children in rural and urban China. Results from instrumental variables regressions show a substantial adverse effect of children's exposure to parental migration on height-for-age Z-scores of left-behind children relative to children who migrate with their parents. Additional results from a standard Blinder-Oaxaca decomposition, a quantile decomposition, 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.

JEL Classification: I10, J61
Keywords: migration, China, children, health, nutrition

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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 can engage in care practices that influence child nutrition and health (Tracey and Polachek 2018).

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 parental migration decisions relate to the nutritional status of both children left behind and children who migrate with their parents. In 2010, approximately 61 million children ages 0-17 were left behind in rural villages, accounting for 38 percent and 22 percent of all rural children and all children nationally, respectively (China Women's Federation Research Team 2013).[3] The number of left-behind children has been increasing rapidly, with, for example, an increase of 2.42 million children from 2005 to 2010. Note that this study defines left-behind children as cases in which both parents or just one (father or mother) have migrated from rural to urban areas while leaving the child behind in the rural village to which the household registration (hukou) belongs.[4] Among the 61 million left-behind children in 2010, 47 percent have had both parents migrate to cities; 36 percent have had just fathers migrate; and 17 percent have had just mothers migrate.

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 household registration 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.

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), with a focus on how children's cumulative exposure to parental migration affects the health outcomes of migrating children relative to left-behind children. Multiple approaches are used to clearly identify these effects, including ordinary least squares regressions, instrumental variables, a standard Blinder-Oaxaca decomposition, and quantile decompositions based on re-centered 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: Rural to Urban Migration 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.

The *hukou* system has also contributed to discrimination in the labor market, with urban migrants who hold rural *hukou* experiencing greater difficulty obtaining higher-paid formal sector jobs, especially in state-owned enterprises (Song 2014). Difficulty in finding high-wage employment in turn has strong implications for the ability of urban migrants with rural *hukou* to send remittances back home, which in turn could impact the well-being of their children left behind. Evidence of this assertion is found in Hannum *et al.* (2014), a study showing 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. In particular, Yang (2013) finds that urban migrants in China with a rural *hukou* have substantially lower socioeconomic status compared to their locally-born counterparts and compared to urban-urban migrants. Socioeconomic status reflects not only earnings and occupation but also access to social insurance and quality housing.

Our analysis of child health also builds on work in Mu and De Brauw (2015), Chen (2013), and Meng and Yamauchi (2017), 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 associated with parental migration outweighs any negative effect of the parents spending 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 improved weight-for-age among children under the age of five, while there is no statistically significant effect on children's height-for-age. However, 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 (2017) use different data – the RUMiC survey – and find that as the the absence of migrant mothers increases in duration, the height-for-age and weight-for-age of rural children ages 15 and below decreases. In contrast, the length of the absence of migrant fathers has a negative and statistically significant effect only on rural children's weight-for-age. In sum, the results on whether parental migration boosts or harms nutritional status of children left behind in China's rural areas are inconclusive. Moreover, none of these previous studies examine children who migrate with their parents to urban areas, thus leaving open the question of the effect of parental migration on the health status of all children in migrant households.

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.[5] The survey covers 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.[6] 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.[7] 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.

Although the RUMiC is a large survey covering thousands of migrant households in multiple cities and regions, the survey contains no sample weights. Given that official residential registration of migrants in cities lags behind the flow of people and reliable information on the migrants' backgrounds and their distribution is incomplete, the biggest challenge of designing an unbiased sampling frame involves how to randomly sample the migrant population (Gong *et al.*

2008). Existing migrant surveys (for example, the China Urban Labour Survey conducted by China Academy of Social Sciences) 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 inherently biased. The RUMiC survey avoids this problem by using a unique sampling frame based on information collected in a census of migrant workers at their workplaces, and the census is conducted across multiple randomly-selected city grids within the city's defined boundary (IZA *et al.* 2014).[8]

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). 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 (2017) analysis of child health outcomes in China. Our regression results do not change substantively when the WHO standards are used.

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. Moreover, according to Kong (2010), both rounds of the survey were administered in the spring and early summer (the first round was conducted February-April 2008 and the second round was conducted March-July 2009), which marks just a month or two after many migrants have returned home for the Spring Festival (that is, the lunar new year). Hence questions asking migrants to recall the height and weight of their children are less likely to be subject to measurement error when most migrants with left-behind children have recently visited their rural hometowns. Another possible concern is that the survey was administered at the same time as the 2008-2009 global financial crisis, which entailed millions of layoffs in China. However, evidence in Chen *et al.* (2011) indicates that children were relatively insulated from the global financial crisis in terms of their nutritional status due to the Chinese government's policy responses to the crisis, which included subsidies for farmers, agricultural price protections, and social security policies. Hence the timing of the survey is unlikely to bias our study's substantive results.

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 higher for children living with their parents. Fewer than half of the children are girls, and about 56 percent of children in migrant households are left behind in rural villages. 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). Note that this variable was constructed for the usual weekly hours worked of the household head and includes household heads who stayed home to care for children and did not work for pay. When we exclude these household heads who stayed home full-time, then the mean number of weekly hours worked is closer to 65, which is in line with the common view that migrants work unusually long hours.

Consistent with published statistics on gender gaps in schooling, Table 1 also shows that 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. Also of interest, on average parents spent about 11 months away from their home towns in the past year, and this duration is higher for children who migrate with their parents. On average, migrants spend about 41 percent of their household expenditures on food. That said, the food share in total household consumption expenditures is lower – and real household income is also considerably higher – for children who migrate with their parents compared to children who are left behind. Finally, the occupational distribution also differs substantially for parents of left-behind children versus parents of children who migrate with their parents. These differentials are particularly large for household heads who are in retail and sales and in self-employment, with proportionately more parents employed in these sectors for children who migrate with their parents compared to children who are left behind. In contrast, children who are left behind are more likely to have parents who work as construction laborers.

IV. Empirical Methodology

Effect of Parental Migration on Child Health

We start the empirical analysis with an OLS and instrumental variables approach to estimating the effects of parental migration on health outcomes of both migrating children and left behind children. Specifically, we estimate the following equation:

$$Y_{ijt} = b_1 B_{ijt-1} + b_2 M_{ijt-1} + b_3 (B_{ijt-1} \times M_{ijt-1}) + b_4 X_{ijt} + b_5 J_j + b_6 T_t + e_{ijt} \quad (1)$$

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, and B_{ijt-1} is an indicator that equals one if parents bring the child with them in year t-1. The notation M_{ijt-1} is the key treatment variable "lifetime exposure to parental migration" which captures the cumulative effect of parental migration on children.[10] Similar to Meng and Yamauchi (2017), we define M_{ijt-1} as the portion of the child's lifetime in which the parents were away from the rural hometown up through year t-1. That is,

$$M_{ijt-1} = \frac{\text{number of months parents were away since the child was born}}{\text{total number of months since the child was born}} .$$

Our focus is the term B_{ijt-1} and the interaction term $B_{ijt-1} \times M_{ijt-1}$. To facilitate interpretation of the results, in the analysis we center the "lifetime exposure to parental migration" variable M_{ijt-1} by taking the deviation of each value from the mean. So the coefficient b_1 is interpreted as the average difference between migrating children with an average lifetime exposure and left-behind children with an average lifetime exposure. The coefficients b_1 and b_3 are also used to calculate the marginal effect (that is, the discrete change) of a change in the "bring the child" variable from 0 to 1, thus capturing the impact of the parental decision to bring the child to live with them in the city on the health outcomes of children.[11]

Also in equation (1), the matrix X represents individual-level and household-level controls, including whether or not the child is a girl, whether or not the household has a rural *hukou*, whether or not the household head is female, whether or not the child is in a boarding school, birthweight, a set of dummy variables for parental occupation (professional & managers, manufacturing, construction laborers, personal services, restaurant and hotel staff, retail and sales, transport & security, self-employed and private business owner, and other), the natural log of household income, 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), height of the household head, and market value of the household's property in their home town. 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.[12] Moreover, the notation J represents region-level fixed effects, and T denotes year fixed effects.[13] Because the survey records multiple children per household as separate observations, we correct the standard errors for clustering at the level of the household.

Since the parental migration decision (whether to bring the child or not) is potentially endogenous, we also use an instrumental variables approach (IV). Because any interaction term that has an endogenous variable is also endogenous, we must use at least two instruments for estimating equation (1). Our instruments include: (i) whether the child lives with grandparent(s) in the rural hometown; and (ii) the first instrument interacted with the lifetime exposure variable. An ideal instrument is a factor that strongly correlates with the 'bring child' variable but does not directly affect child health outcomes except via the decision of bringing the child. Living with grandparents is unlikely to directly change children's health outcomes. In our data, most grandparents are busy working as full-time employees (66% farmers and 22% household or family workers), and 90% of grandparents are in fairly good health status. Hence, we argue that whether living with grandparents is strongly correlated with the 'bring child' decision (as shown in Section V) but does not directly change child health outcomes.

Blinder-Oaxaca Decomposition and Decomposition of Quantile Gaps

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 Blinder-Oaxaca 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 (Blinder 1973; Oaxaca 1973). This decomposition is expressed in vector-matrix form as

$$\begin{aligned}\Delta_t &= \overline{\mathbf{Y}}_t^{LB} - \overline{\mathbf{Y}}_t^{MC} = \overline{\mathbf{X}}_t^{LB}\mathbf{b}_t^{LB} - \overline{\mathbf{X}}_t^{MC}\mathbf{b}_t^{MC} \\ &= \underbrace{(\overline{\mathbf{X}}_t^{LB} - \overline{\mathbf{X}}_t^{MC})\mathbf{b}_t^{LB}}_{\substack{\text{explained gap} \\ \text{(characteristics effect)}}} + \underbrace{(\mathbf{b}_t^{MC} - \mathbf{b}_t^{LB})\overline{\mathbf{X}}_t^{MC}}_{\substack{\text{unexplained gap} \\ \text{(coefficient effect)}}} \qquad (2)\end{aligned}$$

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 (2), 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 (2), a method henceforth referred to as the detailed decomposition, to measure the contribution of every variable in the equation.[14]

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

$$\Delta_t(\tau) = q_t^{LB}(\tau) - q_t^{MC}(\tau). \tag{3}$$

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 re-centered influence function (RIF) in unconditional quantile regressions. Suppose the quantile of interest is $q(\tau)$. Then the re-centered influence function, $RIF_{ijt}(\tau)$, is defined as

$$RIF_{ijt}(\tau) = q(\tau) + [I(Y_{ijt} \geq q(\tau)) - (1-\tau)]/f(q(\tau)), \tag{4}$$

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 (4) 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:

$$RIF_{ijt}(\tau) = b_1 X_{ijt} + b_3 J_j + b_4 T_t + e_{ijt}. \tag{5}$$

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 Blinder-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.[15]

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 $F_{Y_0|X_0}(y \mid x)$ and $F_{Y_1|X_1}(y \mid x)$ 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:

$$F_{Y\langle 0|1\rangle}(y) := \int_{\chi_1} F_{Y_0|X_0}(y \mid x)\, dF_{X_1}(x). \tag{6}$$

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 (6), 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:

$$\Delta^{DE}(y) = F_{Y\langle 1|1\rangle}(y) - F_{Y\langle 0|1\rangle}(y). \tag{7}$$

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 (7), the quantile treatment effect (QTE) on the treated is:

$$QTE(\tau)=Q_{Y\langle 1|1\rangle}(\tau)-Q_{Y\langle 0|1\rangle}(\tau). \tag{8}$$

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.[16]

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

Effect of Parental Migration on Child Health

Table 2 presents the effects of lifetime exposure to parental migration on children's health outcomes. Panel A reports the OLS estimates of WAZ and HAZ scores for both Models (1) and (2), where Model (1) defines migrating children as those who live with parents in the same township and the same city, and Model (2) allows children to live in other townships but still in the same city as their parents. All regressions in Table 2 include a full set of individual and household level characteristics, village and city controls, and region and year fixed effects. Our variables of interest are whether or not the parents bring the child, the lifetime exposure variable, and their interaction. All standard errors are clustered at the household level. The marginal effects calculated from the OLS results indicate that the level of cumulative exposure to parental migration has an adverse effect on HAZ scores (the longer-term health measure) for left-behind children – a 0.28 to 0.32 point difference if migrant parents do not bring the child with them. For WAZ scores (the shorter-term health measure), we find a 0.20 to 0.21 point difference. The OLS results for regressions using deviations from the mean show similar outcomes: the average difference of WAZ and HAZ scores between migrating children with an average lifetime exposure to parental migration and left-behind children with an average lifetime exposure to parental migration is 0.20 to 0.21 points and 0.28 to 0.33 points, respectively.

To address the potential endogeneity of parental migration, we instrument the parental migration variable as well as the interaction term and report the IV results in Panel B of Table 2. We ran two types of Two-Stage Least Squares (2SLS) regressions for both WAZ and HAZ scores. Our first stage results show that coefficients of the instrumental variable "whether the child lives with grandparent(s)" are positive and statistically significant at 5% level, thus satisfying the strong relevance condition of a valid instrument. The F-statistics for the first-stage in the 2SLS(1) and 2SLS(2) models are 12.9 and 12.2, which are above the value of 10 that is generally regarded as the critical value for a viable instrument but are slightly below the value 13.43 of the Stock-Yogo (2005) weak ID test critical values at 10% maximal IV size. This suggests that we may have an issue with weak instruments, which we address by using a Limited Information Maximum Likelihood (LIML) estimator. This estimator is asymptotically equivalent to 2SLS and has been found to outperform 2SLS in finite samples. Based on the LIML estimator, our weak identification test in Table 2 yields a Kleibergen-Paap rk Wald F statistic which is significant at 10% for a Stock and Yogo (2005) maximal IV size with a critical value of 5.44. Given the statistical significance of the Wald F statistic in this identification test, we can consider our instruments as valid, and LIML substantially reduces the concern of weak instruments (Murray 2006). Looking at our IV results, the marginal effects show that cumulative exposure to parental migration has an adverse effect on the HAZ scores of left-behind children – a differential of 0.44 to 0.45 points. The IV estimates of HAZ scores also show similar outcomes: the average difference of HAZ scores between migrating children with an average lifetime exposure and left-behind children with an average lifetime exposure is 0.43 to 0.44 points. For WAZ scores, however, we do not find an effect.

Blinder-Oaxaca Decomposition and Decomposition of Quantile Gaps

The next stage of the analysis entailed Blinder-Oaxaca and quantile decompositions of the gap in WAZ and HAZ scores between left-behind children and children who live with their parents. Table 3 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 virtually 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 of the distribution. At the mean, most of the WAZ gap is explained by differences in characteristics (62 percent), and also most of the HAZ gap is explained by differences in characteristics (67 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 help close the nutritional status gap in the longer term (as indicated by HAZ scores) as well as in the shorter term (as indicated by WAZ scores).

Looking more closely at the quantile decomposition results for the WAZ scores, Table 3 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 unexplained gaps between the two groups of children, as indicated by the column of results for gaps due to coefficients (2). Intuitively, left-behind children who are higher up the distribution of WAZ scores suffer less of a health penalty from relative deficiencies in unobserved characteristics. This conclusion can also be seen in Figure 1, 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 3 and Figure 2 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 from the 10^{th} to the 30^{th} percentiles, the size of the explained gap then fluctuates as one moves up across higher percentiles of the distribution. In contrast, the unexplained gap (the portion due to coefficients) increases from the 10^{th} to the 30^{th} percentiles and then decreases till the top of 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 at the lower end of the distribution. In particular, unobserved characteristics play a more important role in reducing the gap above the 30^{th} percentile.

Table 4 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 observed productivity characteristics rather than coefficients. Of the gap that is explained by characteristics, maternal education is one of the most important determinants of the gap, accounting for about 40 percent of the aggregate effect. Other important contributors to the mean gap between the two groups of children are whether or not the child attends boarding school, lifetime exposure to parental migration, and whether or not the household holds a rural *hukou*. In the case of HAZ scores, the unexplained portion of the mean gap is relatively smaller, at about one third. Of the gap that is explained by characteristics, maternal education again plays the biggest role, accounting for about a quarter of the aggregate effect. Other characteristics that play an important role in explaining the mean gap in HAZ scores are whether or not the child attends boarding school, lifetime exposure to parental migration, and household income.

Counterfactual Distributions

The final set of results is found in Table 5 and Figures 3 to 4, 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 10^{th} and the 20^{th} 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 20^{th} percentile.

In contrast, the treatment effects for the HAZ scores are statistically significant along the entire quantile distribution except the 90^{th} percentile. We do not reject the null hypotheses that our parametric conditional model is correctly specified and that 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 4 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 terms of their height-for-age) if they were to live with their parents in cities.

VI. Policy Lessons

This study is 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. We find 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. Results also point to a sizable adverse effect of cumulative exposure to parental migration on HAZ scores of left-behind children. A quantile decomposition procedure indicates that the health 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. Overall our results point to the importance of policies that discourage parents from leaving their children behind, especially a revision of the *hukou* system so that migrating households are no longer denied public services in destination cities. Improving the accessibility of public education and health services in urban areas for migrants will make it more likely that parents bring their children with them.

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. 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.

Finally, it is imperative that the government improve the standard of living for rural families 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). Another issue is that numerous rural localities have consolidated their school districts by closing some schools and turning other into boarding schools. However, research shows that children living in these boarding schools have a higher incidence of malnutrition than non-boarding rural students (Luo *et al.* 2009). Policy reforms that improve access to schools, raise the quality of education, provide incentives to remain in school such as free lunch programs, and improve the health and nutritional status of children who board at 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-family as well as pro-growth.

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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
Individual and household controls						
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
Lifetime exposure to parental migration	.858	.252	.835	.273	.890	.213
Avg. number of months last year parent(s) away	11.344	1.737	11.136	2.034	11.650	1.101
Household income (annual, real)	2889.69	1981.95	2559.02	1930.02	3307.60	1968.41
Log household income (annual, real)	7.805	.564	7.680	.558	7.961	.530
Birthweight (kg)	3.326	.543	3.318	.545	3.339	.539
Boarding school	.172	.377	.251	.434	.067	.250
Food share in total consumption	41.343	17.133	43.884	18.362	38.132	14.836
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
Market value of hometown properties/assets (log, real)	10.131	1.736	10.159	1.573	10.094	1.929
Occupation of HH head (%)						
Professionals & managers	2.16		1.99		2.38	
Manufacturing	8.28		10.08		6.02	
Construction laborers	11.47		16.56		5.04	
Personal services	11.38		12.02		10.57	
Restaurant and hotel staff	5.16		6.53		3.43	
Retail and sales	17.71		12.96		23.72	
Transport & security	14.13		17.94		9.31	
Self-empld and private business owner	20.99		12.96		31.14	
Others	8.72		8.97		8.40	
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. Impact of Parental Migration on Child Health

A. OLS Estimates and Marginal Effects of Lifetime Exposure to Parental Migration on Child Health

Dependent variable: WAZ and HAZ	Weight-for-Age Z-scores		Height-for-Age Z-scores	
	Model (1)[a]	Model (2)	Model (1)	Model (2)
Marginal effects of Bring the child	.202**	.212**	.277**	.323***
	(.084)	(.088)	(.114)	(.119)
OLS results (selected)				
Bring the child	.202**	.212**	.280**	.325***
	(.085)	(.089)	(.114)	(.119)
Lifetime exposure	.195	.199	-.027	-.014
	(.167)	(.167)	(.212)	(0.212)
Bring the child × Lifetime exposure	-.073	-.047	.767**	.913**
	(.267)	(.275)	(.365)	(.380)
Individual and household level characteristics	Yes	Yes	Yes	Yes
Village and city controls	Yes	Yes	Yes	Yes
Region and year fixed effects	Yes	Yes	Yes	Yes
Adj. R^2	.087	.089	.098	.094

B. IV Estimates and Marginal Effects of Lifetime Exposure to Parental Migration on Child Health

Dependent variable: WAZ, HAZ	Weight-for-Age Z-scores			Height-for-Age Z-scores		
Estimator: 2SLS, LIML	2SLS (1)	2SLS (2)	LIML	2SLS (1)	2SLS (2)	LIML
Marginal effects of Bring the child	.120	.119	.120	.438**	.448**	.450**
	(.129)	(.128)	(.129)	(.176)	(.176)	(.188)
IV results (selected)						
Bring the child	.121	.120	.121	.431**	.441**	.442**
	(.124)	(.123)	(.124)	(.173)	(.173)	(.184)
Lifetime exposure	1.018	.952	1.026	-.661	-.692	-.931
	(1.968)	(1.965)	(1.995)	(2.600)	(2.593)	(3.022)
Bring the child × Lifetime exposure	-.672	-.582	-.682	1.421	1.455	1.779
	(2.600)	(2.597)	(2.636)	(3.456)	(3.448)	(4.015)
First stage results (selected)						
Dependent variable: Bring the child						
Live with grandparent(s)	.069***	.067***	.069***	.060**	.059**	.060**
	(.024)	(.024)	(.024)	(.024)	(.024)	(.024)
Live with grandparent(s) × Lifetime exposure	-.110***	-.110***	-.110***	-.109**	-.109**	-.109**
	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)
Individual and household level characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Village and city controls	Yes	Yes	Yes	Yes	Yes	Yes
Region and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Weak identification test[b]						
Kleibergen-Paap rk Wald F statistic	12.899	12.980	12.899	12.161	12.270	12.161
Number of instrumental variables used	2	2	2	2	2	2

Note: The lifetime exposure variable has been centered by taking the deviation of each value from the mean. Standard errors, in parentheses, are clustered at the household level; whereas the standard errors of marginal effects are calculated by the delta method. The notation *** is $p < 0.01$, ** is $p < 0.05$, * is $p < 0.10$. The numbers of observation for Model (1) and Model (2) are 2251 and 2254, respectively. Marginal effects are discrete changes of Bring the child variable from the base level 0 to 1 and are estimated at the means of covariates. 2SLS and LIML stand for the two-stage least squares and the limited-information maximum likelihood estimators, respectively. Two instruments are 1)whether children live with grandparent(s) and 2)interaction of whether children live with grandparent(s) and lifetime exposure.

[a] Model (1) defines migrating children as those who live with parents in the same township and the same city. Model (2) defines migrating children as those who live with parents in the same city but can be in other townships. LIML estimations use the definition of Model (1).

[b] For 2SLS, the Stock-Yogo (2005) weak ID test critical values at 10% and 15% maximal IV sizes are 13.43 and 8.18, respectively. For LIML, the Stock-Yogo (2005) weak ID test critical values at 10% and 15% maximal LIML sizes are 5.44 and 3.81, respectively.

Table 3. Mean and Quantile Decompositions of Differences in WAZ and HAZ Distributions between Left-Behind Children and Children Who Live with Their Parents

Dependent variable	Weight-for-Age Z scores (WAZ)			Height-for-Age Z scores (HAZ)		
Mean/ Quantile(τ)	Raw difference	Due to (1) Characteristics	Due to (2) Coefficients	Raw difference	Due to (1) Characteristics	Due to (2) Coefficients
Mean	-.199*** (.057) [100]	-.123*** (.037) [61.81]	-.076* (.045) [38.19]	-.650*** (.073) [100]	-.434*** (.047) [66.77]	-.216*** (.059) [33.23]
.10	-.413*** (.067) [100]	-.142* (.139) [34.38]	-.271*** (.084) [65.62]	-.993*** (.071) [100]	-.613*** (.213) [61.73]	-.380*** (.123) [38.27]
.20	-.408*** (.049) [100]	-.166*** (.117) [40.69]	-.242*** (.053) [59.31]	-.986*** (.075) [100]	-.484*** (.183) [49.09]	-.502*** (.088) [50.91]
.30	-.333*** (.047) [100]	-.151*** (.105) [45.35]	-.182*** (.047) [54.65]	-.843*** (.068) [100]	-.320*** (.164) [37.96]	-.523*** (.072) [62.04]
.40	-.268*** (.043) [100]	-.142*** (.101) [52.99]	-.126*** (.041) [47.01]	-.731*** (.054) [100]	-.290*** (.144) [39.67]	-.441*** (.057) [60.33]
.50	-.211*** (.040) [100]	-.129*** (.102) [61.14]	-.082* (.047) [38.86]	-.651*** (.053) [100]	-.270*** (.127) [41.47]	-.381*** (.059) [58.53]
.60	-.162*** (.044) [100]	-.110** (.037) [67.90]	-.052 (.045) [32.10]	-.601*** (.052) [100]	-.286*** (.117) [47.59]	-.315*** (.054) [52.41]
.70	-.126*** (.043) [100]	-.083 (.042) [65.87	-.043 (.050) [34.13]	-.531*** (.052) [100]	-.279*** (.112) [52.54]	-.251*** (.059) 47.27]
.80	-.067 (.047) [100]	-.032 (.115) [47.76]	-.035 (.057) [52.24]	-.451*** (.052) [100]	-.245*** (.113) [54.32]	-.206*** (.074) [45.68]
.90	.037 (.065) [100]	-.003 (.132) [-8.11]	.040 (.072) [108.11]	-.367*** (.067) [100]	-.205** (.127) [55.86]	-.162* (.087) [44.14]

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 $p < 0.01$, ** is $p < 0.05$, * is $p < 0.10$.

Table 4. Detailed Decomposition of Mean Differences in WAZ and HAZ Scores between Left-Behind Children and Children with Parents

Dependent variable: 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	$-.123^{***}$	61.81	$-.076^{*}$	38.19	$-.434^{***}$	66.77	$-.216^{***}$	33.23
Individual & household controls	$-.140^{*}$	70.41	.304	-152.66	-.250	38.49	1.638	-251.99
Rural *hukou*	$-.016^{*}$	7.99	-.443	222.16	-.003	0.46	.014	-2.13
Female-headed HH	-.003	1.43	.065	-32.43	-.015	2.35	.031	-4.77
Child is a girl	.005	-2.37	-.049	24.54	.001	-0.18	.081	-12.42
Birthweight	-.001	.41	-.147	73.59	-.001	0.12	-.360	55.34
Lifetime exposure	$-.019^{**}$	9.51	.164	-82.25	$-.025^{**}$	3.89	$-.729^{***}$	112.11
Household income	.014	-6.99	-.852	427.38	$-.059^{**}$	9.09	.339	-52.12
Food share in consumption	.009	-4.28	-.029	14.56	-.004	0.58	-.193	29.71
Boarding school	$-.046^{***}$	23.06	-.017	8.44	$.034^{**}$	-5.18	.001	-0.22
Usual hours worked	-.003	1.42	-.044	21.88	-.001	0.21	-.040	6.20
Mother’s years of education	$-.081^{***}$	40.81	-.015	7.46	$-.154^{***}$	23.68	.151	-23.26
Father’s years of education	-.014	6.89	-.148	74.44	-.020	3.09	-.353	54.38
Age of HH head	.011	-5.76	.596	-299.09	-.004	0.54	1.401^{**}	-215.51
HH head has Han ethnicity	-.005	2.66	$-.638^{*}$	320.23	-.009	1.39	-.672	103.44
Height of HH head	.007	-3.72	1.874	-940.50	.009	-1.45	2.055	-316.15
Market value of hometown assets	.001	-.66	-.014	6.93	.001	-0.11	$-.087^{*}$	13.42
Occupation controls	-.000	.20	$.082^{*}$	-41.18	-.037	5.69	.053	-8.13
Village controls	.005	-2.49	.275	-137.99	.015	-2.31	.455	-69.98
City controls	.038	-18.98	-3.424	1718.3	$.084^{***}$	-12.92	-2.991	460.18
Year & Region fixed effects	-.025	12.62	.037	-18.57	$-.246^{***}$	37.81	.080	-12.26
Constant			2.650	-1329.7			.550	-84.58

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 5. Quantile Treatment Effects of Counterfactual Distribution Estimations and Inferences

Dependent variable: Child Anthropometric Measures	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	.218*	.118	.263***	.126
.20	.149*	.089	.404***	.111
.30	.115	.079	.319***	.099
.40	.091	.070	.249***	.088
.50	.077	.067	.251***	.085
.60	.066	.068	.252***	.085
.70	.053	.070	.235***	.090
.80	.049	.075	.252***	.113
.90	.031	.088	.333	.222

Bootstrap inference on the counterfactual quantile processes

Null hypothesis	P-values (WAZ)		P-values (HAZ)	
	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	.392	.320	.040	.012
(3) Constant effect: QTE(τ)=QTE(.5) for all τ	.818	.650	.626	.708
(4) Stochastic dominance: QTE(τ)>0 for all τ	.836	.836	.876	.876
(5) Stochastic dominance: QTE(τ)<0 for all τ	.216	.184	.036	.012

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 $p < 0.01$, ** is $p < 0.05$, * is $p < 0.10$.

Figure 1. Quantile Decomposition Results for WAZ-Score Gaps between Left-Behind Children and Children Who Live with Their Parents

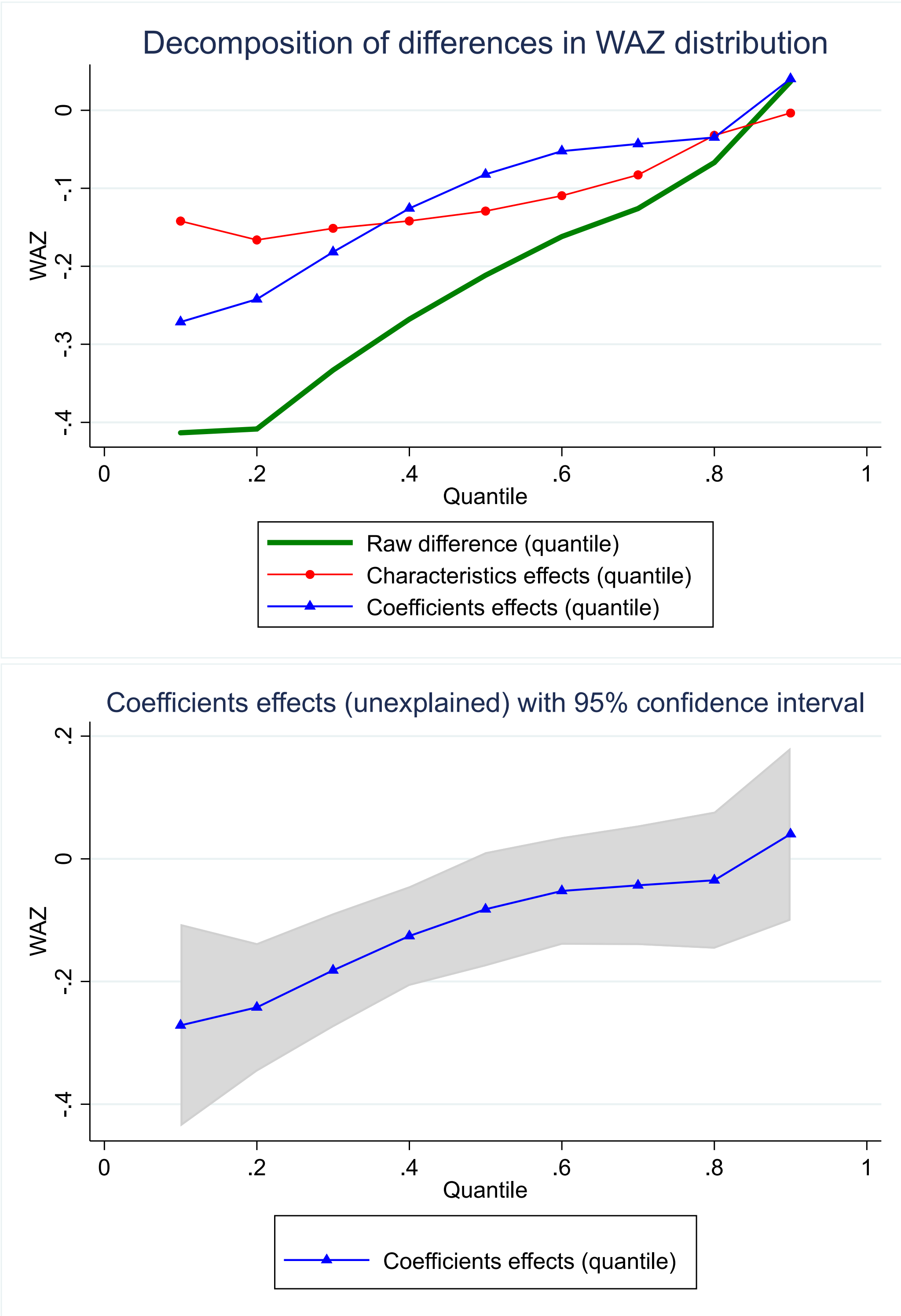


Figure 2. Quantile Decomposition Results for HAZ-Score Gaps between Left-Behind Children and Children Who Live with Their Parents

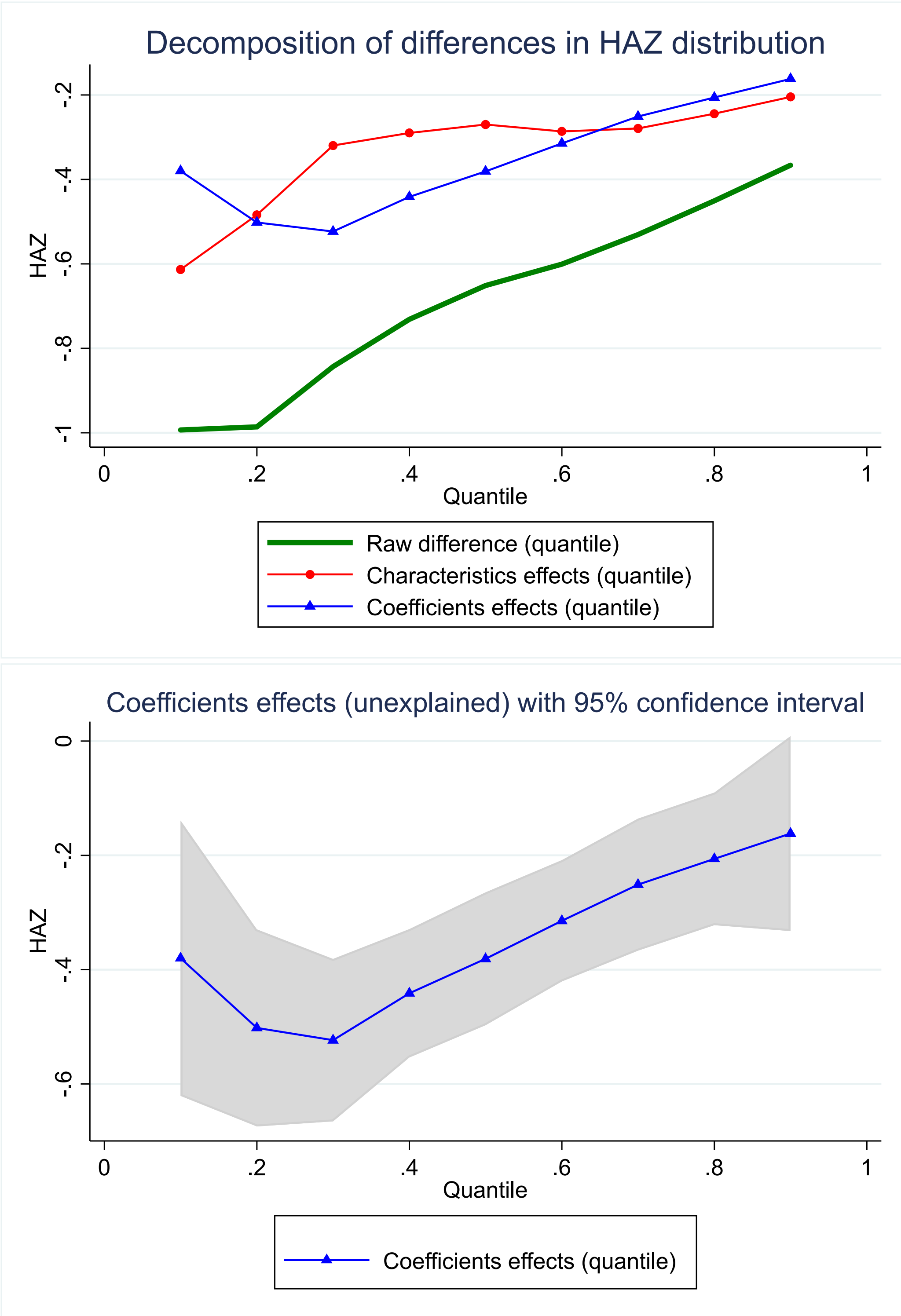
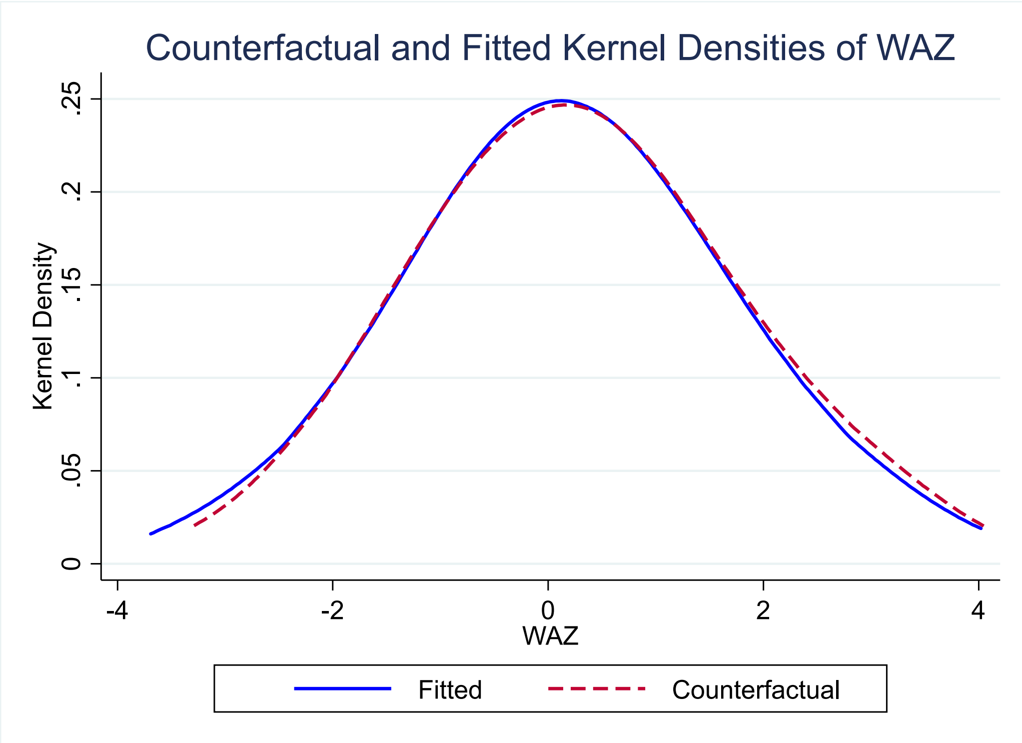


Figure 3. Counterfactual Quantile Treatment Effects for WAZ Scores



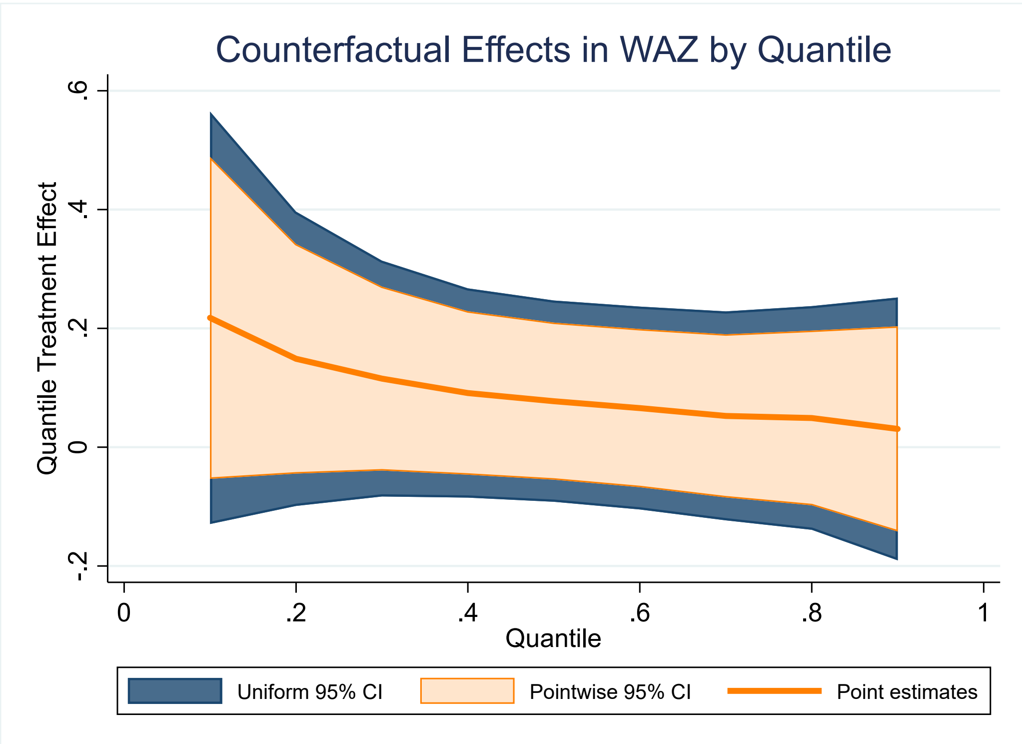
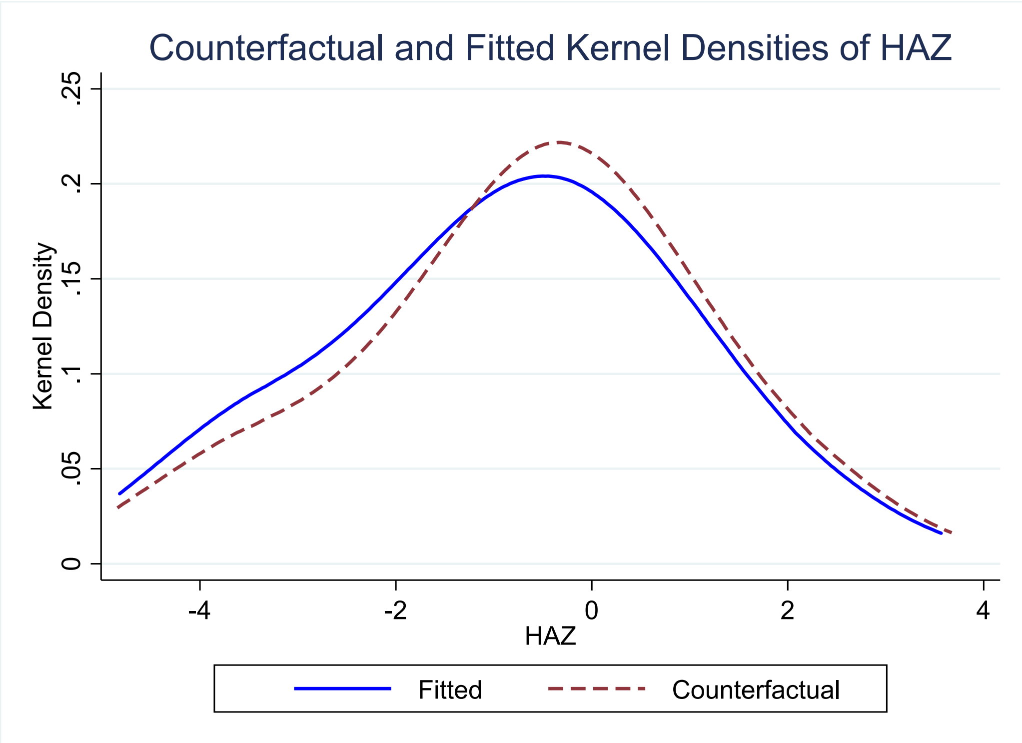
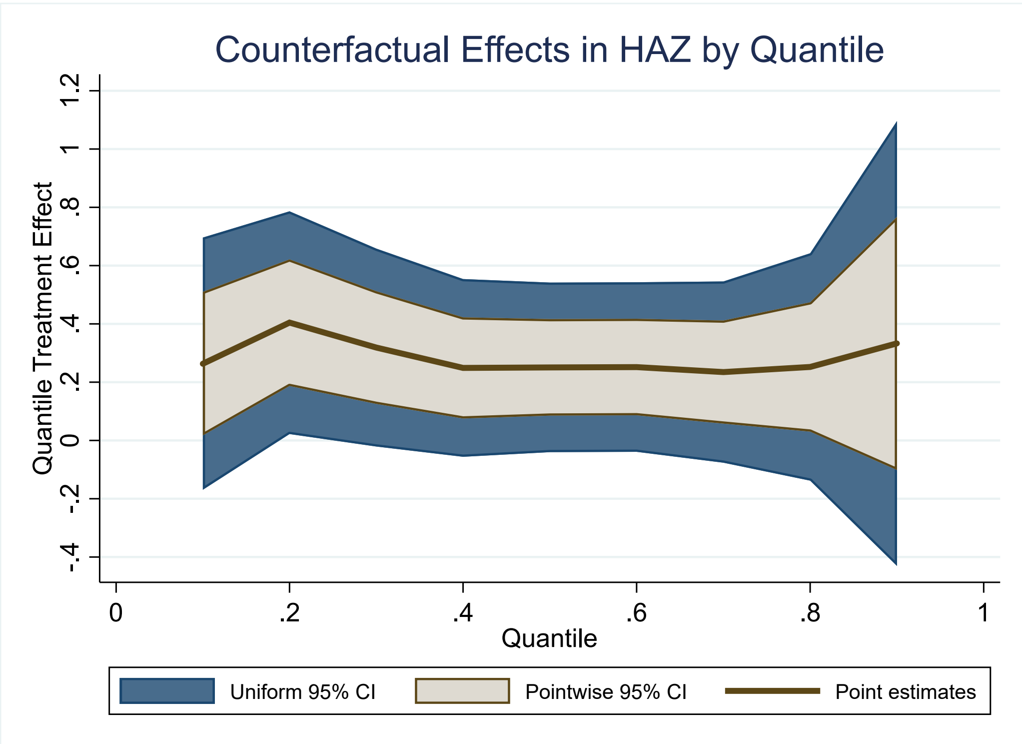


Figure 4. Counterfactual Quantile Treatment Effects for HAZ Scores





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] The study defines left-behind children as cases in which both parents or just one (father or mother) have migrated from rural to urban areas while leaving the child behind in the rural village to which the household registration (*hukou*) belongs. Among the 61 million left-behind children in 2010, 47 percent have had both parents migrate to cities; 36 percent have had just fathers migrate; and 17 percent have had just mothers migrate. Our paper uses the same definition.

[4] As a robustness check, we created four separate categories of left behind children: all left behind children, both parents work in city and leave child behind; mother works in city and child is left-behind with father; and father works in city and child is left behind with mother. We then created a set of kernel density graphs showing difference between migrating children and children in each of these categories. These graphs (available upon request) show that the differences in HAZ and WAZ scores between the four categories of left behind children are negligible.

[5] 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).

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

[7] 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)?"

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

[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] We also consider "contemporaneous parental migration" defined as the average number of months the mother and/or father was away in year *t*-1 to study the short-run effect of parental

migration on children's health. The coefficient on the key interaction term is only statistically significant for WAZ scores, Model 2, at the 10 percent level. These results are available upon request.

[11] Suppose there are no other covariates and fixed effects in equation (1). If $B=0$, then $y=b_2M$; and if $B=1$, then $y=b_1+(b_2+b_3)M$. Hence, the marginal effect of the discrete change from the base level ($B=0$) is b_1+b_3M. In other words, this is the marginal effect of the parents' decision to migrate with the child. In the analysis, we compute the marginal effect at the means of the covariates.

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

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

[14] 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 (Horrace and Oaxaca 2001; Gardeazabal and Ugidos 2004; Yun 2005; and 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).

[15] 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 Blinder-Oaxaca decompositions.

[16] 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.