HHS Public Access
Author manuscript
Eur Sociol Rev. Author manuscript; available in PMC 2016 March 14.

Published in final edited form as:
Eur Sociol Rev. 2015 ; 2015: . doi:10.1093/esr/jcv009.

The Causal Effects of Rural-to-Urban Migration on Children's Wellbeing in China

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Abstract

China's rural-to-urban migration has affected 12.6 million school-age rural children who have migrated with their parents and another 22 million who have been left behind by their migrant parents. Not enough is known, either theoretically or empirically, about the causal impact of migration on the wellbeing of this large number of Chinese children affected by migration. Propensity score matching methods are applied to estimate the effects of migration in children 10–15 years old from a 2010 national survey (N = 2,417). Children's migration has significant positive effects on their objective wellbeing but no negative effects on their subjective wellbeing. There is little difference between the left-behind and non-migrant children across multiple life domains. The Rosenbaum bounds tests indicate that the causal effects of child migration are sensitive to hidden bias for certain outcomes, but not for others.

Keywords

Migration; children; China; propensity score matching

INTRODUCTION

China's rural-to-urban migration, like that in many developing countries, is often temporary and circular, with children either moving along with their parents to cities or being left behind in the countryside. According to a report by the Ministry of Education of China (MOE2012), over 12.6 million school-age rural children had migrated with their parents in 2011, an 8% increase over the 2010 figure. At the same time, another 22 million children had been left behind by their migrant parents. While much work has been devoted to documenting the huge number of children involved in China's ongoing large-scale migration process, not enough is known, either theoretically or empirically, about the causal impact of migration on children's wellbeing.

Most of the relevant studies to date have compared migrant children to their urban native peers, an inappropriate reference group for understanding the true causal impact of migration. Since they have been socioeconomically advantaged for decades, urban Chinese children are not only better off at birth in nearly every relevant respect, ranging from nutrition to neonatal health care and from family socioeconomic status to parenting knowledge and behavior, but also exposed to resource-rich environments (e.g. neighborhoods and schools) and more policy benefits (e.g. dependent medical insurance from their parents' work units) as they grow up. The assimilation model, based largely on the literature on immigrants to the U.S. (Greenman and Xie 2008; Zhou 1997), may help us predict the narrowing gap in wellbeing between rural-to-urban migrant children and their urban-born peers over the period since migration, but the assimilation model does not tell us anything, counterfactually, about the causal impact of migration on rural-to-urban migrant children.

From a causal inference perspective, it is inappropriate to use urban children as a reference group for assessing the causal effects of rural-to-urban migration. As Holland (1986) puts it, "For causal inference, it is critical that each unit be *potentially exposable* to any one of the causes. As an example, the schooling a student receives can be a cause…of the student's performance on a test, whereas the student's race or gender cannot." Likewise, to the extent that the notion of being "potentially exposable" does not apply to urban children who are, by definition, not at risk for rural-to-urban migration, our understandings about the causal effect of this treatment would remain elusive if we continued to mistakenly treat urban children as the control group.

It is worth noting that Holland's (1986) strong view of "no causation without manipulation" led him to consider only factors that can, in principle, be manipulated in experiments as legitimate causes. Thus, not only are personal attributes such as sex and race ruled out as potential causes, but voluntary activities such as studying for an exam or migration are also problematical causes. In this study, we do not treat manipulability as a decisive exclusive criterion. Instead, we concur with Ní Bhrolcháin and Dyson (2007) that factors with a voluntary aspect may still constitute candidate causes in social science, provided that they satisfy certain criteria supportive of causal inference. Rural-to-urban migration in this study meets some of the most important criteria proposed by Ní Bhrolcháin and Dyson (2007). For example, migration as a potential cause precedes, in principle, its effects on children's wellbeing (*time order*); a number of plausible mechanisms are proposed to explain how migration brings about its various effects (*mechanism*) and each mechanism predicts a directional effect (*direction*); differences in wellbeing between migrant and non-migrant children who differ only in their treatment status indicate no alternative explanations (*no alternative*).

In studies of U.S. migration, Landale and colleagues (Landale and Hauan 1996; Landale and Oropesa 2001; Singley and Landale 1998) are among the few exceptions that compare migrants to the U.S. with non-migrants living in their places of origin. Their earlier work pooled data from two separate samples, one for non-migrants in Puerto Rico (the origin) and one for migrants in the State of New York (the destination). Their more recent work drew upon data from an integrated survey that sampled respondents from both places of origin and destination. In the context of contemporary China, Liang and colleagues (2007) compared school enrollment rates between migrant and non-migrant children at the place of origin, in addition to local children in cities of Guangdong Province, drawing data from the 1995 China 1% Population Sample Survey.

Capitalizing on data from the 2010 baseline wave of the *China Family Panel Studies* (CFPS), a newly launched nationally representative longitudinal data collection project, we seek to separate out three groups of rural-origin children: those living in non-migrant families, those who are left behind, and those who have migrated with parents. Through appropriately designed comparisons, we adopt a counterfactual causal inference framework to estimate the effects of rural-to-urban migration on rural Chinese children's wellbeing, achievement, and development. Our study contributes to the literature in several important ways. First, with propensity score matching (PSM) techniques, we attempt to estimate the causal effects of migration on child wellbeing in China, a context characterized by large-scale internal migration which is shared by many other developing countries (Toyota, Yeoh and Nguyen 2007). Second, the causal analysis focuses explicitly on the comparison of children of rural origin across different destinations and parental migration experiences. Third, through comparison between the left-behind children and those who migrated with their parents, we decompose the gross effects of migration into two parts: the socioeconomic resources resulting from parental migration and the benefits from co-residence with parents. Fourth, we recognize the fact that migration may be beneficial for children's wellbeing in one domain but detrimental in another (Greenman and Xie 2008). Thus, by examining a wide range of indicators for children's objective and subjective wellbeing and development, we expand upon previous studies that typically focus on one or two aspects such as education and delinquent behavior. Collectively, these extensions draw a more complete picture of migration processes and consequences for China's children.

THEORETICAL BACKGROUND

Like other developing countries, the rural-urban divide is one of the most fundamental socioeconomic and demographic markers and a major driving force behind inequalities in China (Liu, Hsiao and Eggleston 1999; Wu and Treiman 2004). Despite the institutional changes such as the de-collectivization of agriculture and the loosened migration restrictions that have sparked social and economic development in rural China during the past three decades, the rural Chinese remain largely disadvantaged compared to their urban peers in nearly every aspect of life. In fact, rapid economic reforms since the late 1970s have arguably benefited rural and urban populations to different extents, resulting in widened socioeconomic inequalities (Meng 2000; Yang 1999; Zhao 2006). Therefore, it is not surprising that the rural-urban gap in children's wellbeing remains large (Adams and Hannum 2005; Short, Xu and Liu 2013).

We expect the rural-to-urban migration to have a positive impact on bridging the rural-urban gap such that the migrant children would fall somewhere in between in terms of their wellbeing. The classical assimilation theory predicts an upward social mobility process as migrants and their offspring gradually adapt themselves to the hosting environment and benefit from a better opportunity structure at their destinations relative to their places of origin (Warner and Srole 1945). Even though the pathway of assimilation is likely to be segmented, and children of migrants may be confronted by, for example, concentrated residence in urban enclaves, reduced economic opportunities, and emerging oppositional social environment (Zhou 1997), they can still resort to unique resources such as social capital to adapt and overcome these challenges and achieve upward mobility, especially in terms of education (Greenman and Xie 2008).

What remains unclear is to what extent the experience of migration would narrow the preexisting rural-urban gap for migrant children. This conceptual question can be visualized as shown in Figure 1. The horizontal line represents a measure of wellbeing, with rural children at the low end, urban children at the high end, and migrant children in between. Two competing scenarios of the effect of migration can be formulated, depending on where the wellbeing of migrant children falls relative to those of rural children and urban children.

Scenario 1: Migration has little or no effect on narrowing the rural-urban gap so that migrant children are close to non-migrant children of rural origins in terms of wellbeing.

Scenario 2: Migration has a positive effect on narrowing the rural-urban gap so that migrant children are close to urban children in terms of wellbeing.

Empirical assessment of whether Scenario 1 or 2 is true is significant for theoretical understanding of the potential roles of rural-urban migration in bridging the longstanding structural divide between rural and urban China. If Scenario 1 is true, migration does not narrow rural-urban inequality, as migrants do not fare better than other rural residents in the long term. If Scenario 2 is true, however, migration serves as an assimilation process through which rural Chinese gradually close the large social gap between themselves and urban Chinese. In western societies, assimilation is generally considered a multi-faceted process that involves acculturation (adoption of the cultural habits of the host society), structural assimilation (entry into social groups and institutions of the host society), and spatial assimilation (integrated residential distribution with the ethnic majority) (Greenman and Xie 2008). In the context of rural-to-urban migration in China, these features may be loosely translated into adoption of urban lifestyles, access to public resources of quality (e.g. education and medical care), and living in urban neighborhoods characterized by modern utility infrastructure (e.g., tap water, electricity, and cooking gas) and convenient transportation. Walking through these steps is in itself an empowering experience that allows rural Chinese to obtain socioeconomic statuses comparable to those of urban Chinese.

Previous studies are inconclusive as to which of the two scenarios holds true in reality. On the one hand, research tends to support Scenario 1 when based on comparisons of left-behind children to those in non-migrant families (Lau and Li 2011), or migrant children to their urban native peers (Meyerhoefer and Chen 2011). On the other hand, empirical studies that employed detailed information on migration histories or an origin-destination framework have found some evidence supporting Scenario 2, with migrant children having improved educational performance (Chen et al. 2009), similar school enrollment rates as their native-born peers at destination (Hirschman 2001; Liang, Guo and Duan 2008), and lower infant mortality rates (Landale, Oropesa and Gorman 2000).

We argue that only by making appropriate comparisons among different child subgroups can we properly evaluate the causal effects of migration on children's wellbeing. In Table 1, we present a typology of three distinct groups of rural-origin children, cross-classified by parental migration status and child's migration status. We consider three types: Type A: non-migrant children of non-migrant parents; Type B: left-behind children of migrant parents; Type C: migrant children of migrant parents. It is theoretically possible but practically rare for rural-origin children to migrate to cities on their own, leaving their parents behind in the countryside (Type D; N = 15). Thus, we do not include this uncommon group in our study. It is also worth noting that among the left-behind children, some parents may merely move to the urban area within the same county (Type B1; N = 22) and may not negatively affect children's wellbeing due to co-residence, or the lack thereof. Our discussion below refers to the left-behind children as those whose parents migrate to another county (Type B2; N = 401).

We conceptualize two counterfactual models to understand the causal impact of migration on children. First, we compare rural children who are left behind by their migrant parents (Type B) and rural children living with non-migrant parents (Type A). Since both groups of children have stayed in the countryside, the comparison sets up the counterfactual model for assessing *the causal effects of parental migration on rural children's wellbeing*. Second, we compare children who have moved to cities with their migrant parents (Type C) to non-migrant children with non-migrant parents (Type A). Since both groups of children live with their parents in similar nuclear-family environments, the comparison sets up the counterfactual model for assessing the *causal effects of family migration on rural children's wellbeing*.

It is also feasible to compare left-behind children (Type B) and migrant children (Type C). However, this comparison is confounded by two additional causal mechanisms besides child migration: remittances due to parental migration and family structure. Our exploratory analysis indicated few significant differences between these two groups, likely due to their small sample sizes (N = 423 and 209 for Type B and C, respectively). We therefore do not pursue this comparison in the present study. It has been repeatedly shown, in both China and other countries, that the remittances sent back home by migrant workers increase household income, reduce poverty, and thereby contribute positively to children's education and development (Chen et al. 2009; Du, Park and Wang 2005; Edwards and Ureta 2003) Therefore, we expect both the left-behind (Type B) and the migrant children (Type C) to benefit from increased economic resources contributed by adult migrant workers and to be generally better off than rural children in non-migrant households (as indicated by the plus and minus signs in Table 2). However, these benefits come with a price. Staying at home in a rural area with their migrant parents living in cities far away, left-behind children are susceptible to reduced parental care and/or supervision and hence are more at risk for psychological and behavior problems. Studies based upon small sample data in China revealed that the left-behind children often experienced difficulty adapting to life without parents nearby, felt abandoned, and had trouble expressing feelings or obtaining help (Xiang

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2007). One study that employed measurements from clinical psychology reported that compared to those urban natives who lived with their parents in cities, the left-behind children were more likely to be diagnosed with obsessive-compulsive disorder, depression, anxiety, and paranoia (Huang 2004). Moreover, left-behind children were more likely to skip or drop out of school and to complete fewer years of schooling due to less parental supervision or increased time spent on housework and farming to substitute for the absence of adult labor (Battistella and Conaco 1998; Liang, Guo and Duan 2008; McKenzie and Rapoport 2011).

Being a migrant is itself a double-edged sword for rural-origin children. On the one hand, migration to cities exposes children to an urban environment that is characterized by new ideas, more permissive social norms, expanded peer networks, and a wider pool of potential resources, including but not limited to quality schools and teachers, nutrition-rich food environments, and modern hospitals, all of which contribute positively to children's wellbeing and development. In these respects, migration can be an empowering experience for children (Luke et al. 2012). On the other hand, migrant children are confronted by the challenge of assimilating into a new social environment which is somewhat alien to and perhaps even discriminatory towards them. The disruption from the rural culture in which they were born can be extremely detrimental. Migrant children may hence develop risk-taking behaviors and compromise their subjective wellbeing. In a U.S. study, Greenman and Xie (2008) found that in general, Hispanic and Asian immigrant adolescents were more academically successful but also experienced more psychological disturbances (low self-esteem and depression) and engaged in more risky behaviors (delinquency, violence, substance use, and early sexual debut). Nonetheless, evidence of negative consequences for migrant children, especially in developing countries, remains inconclusive. For instance, in Sub-Saharan Africa, adolescents who experienced multiple residential changes may have become more acclimated to life disruptions over time and thus have a lower risk of initiating early sexual intercourse (Luke et al. 2012). Another study of primary school children in Shenzhen, a popular migration destination in China, found no significant difference between migrant children and urban natives in their subjective wellbeing as measured by self-reported happiness, pressures from schoolwork, and self-rated health status (Lau and Li 2011). In fact, one study of three southern provinces suggested that rural parents neither pay close attention to their children's schooling nor are they able to provide them with extra-curricular tutoring (Zhu, Li and Zhou 2002). On the contrary, migrant children may benefit from co-residing with their parents in addition to increased family wealth. Therefore, we would expect migrant children to do better academically than their peers who stay in rural areas with their non-migrant parents.

Furthermore, the assimilation process in urban China may be hindered by institutional barriers such as the household registration system that substantially restricts the opportunities for migrant children to enroll, for example, in public schools of quality and in the health care system (Liang, Guo and Duan 2008). As a result, migrant children may not have direct access to resources available to urban children but instead have to be enrolled in unlicensed migrant-sponsored schools (Lu and Zhang 2001) and face disease risks without immunization coverage (Liang, Guo and Duan 2008). However, there has not been much empirical evidence so far in support of harmful effects of migration on children (Chen et al. 2009).

To summarize, we aim to examine whether rural-to-urban migration has an impact on rural-origin children's wellbeing and if so, to what extent the enduring rural-urban gap can be narrowed as a result of migration. We estimate the effects of migration by matching non-migrant children with non-migrant parents (Type A) with left-behind children (Type B) and migrant children (Type C) on the propensity scores of migration, respectively. We further assess the reduced rural-urban gap resulting from migration by matching migrant children with their urban native peers to gain supplementary evidence for gauging Scenario 1 versus Scenario 2.

DATA

This study draws upon data from the 2010 baseline survey of the China Family Panel Studies (CFPS), a nationally representative longitudinal survey of Chinese communities, families, and individuals. The studies focus on the economic, as well as the non-economic, wellbeing of the Chinese population, with a wealth of information covering such topics as economic activities, education outcomes, family dynamics and relationships, migration, and health. Covering both children at rural origins (either in non-migrant families or left-behind) and those at urban destinations, the CFPS data allow us to fully capture the effects of migration across a wide range of outcomes with a battery of measures of both objective and subjective wellbeing,

The CFPS baseline survey successfully interviewed 14,960 households from 635 communities, including 33,600 adults and 8,990 children, in 25 designated provinces, for an approximate response rate of 81%, with the majority of the non-response due to non-contact. The stratified multi-stage sampling strategy ensures that the CFPS sample represents 95% of the total population in China in 2010 (Xie 2012). The CFPS considered a person at age 15 or younger as children. In this study, we focus on children between age 10 and 15 because this is the only age group who received person-to-person interviews. The CFPS collected limited information by proxy on 5,526 children of 0–9 years old, of whom 2,183 were of schooling ages (6–9).

We have conducted preliminary evaluations of the data quality of the CFPS 2010 by comparing against the data from the 2010 Census and the China General Social Survey (CGSS) in 2010, with respect to important socioeconomic and demographic variables. We found that distributions of age, sex, rural-urban stratification, educational attainment, and marital status in the CFPS resemble those in the census closely. The CFPS data also share similar distributions of household type, size, and income with the CGSS data. This data quality assessment assures us that we can make reasonable generalization of our empirical findings to the Chinese children.

Dependent Variables

We examine a comprehensive list of outcomes across different child development domains, ranging from educational performance to political knowledge, from psychological wellbeing to inter-personal relationships, and from time use to nutrition outcomes (see the list with variable definitions in Table 3). Most of these variables are constructed from multiple items in the survey. We also take advantage of the interviewers' observational data to corroborate measures based on children's self-reports. To our knowledge, some variables such as cognitive achievement were measured for the first time in a nationally representative sample in social science surveys in China.

Treatment and Matching Variables

We define migration status by comparing current type (rural vs. urban) of household registration ("*hukou*") (Chan and Zhang 1999; Cheng and Selden 1994) with current type of residence (rural vs. urban) as well as comparing place of birth with current place of residence at the county level. An urban *hukou* remains an influential factor in determining access to a variety of institutional resources and civil rights as well as a key indicator of permanent legal urban residential status, although its overall influence has weakened in the past decade (Chan and Buckingham 2008; Wang 2004). To simplify analysis, we combine intra- and inter-county migration and focus on rural-to-urban migration only. Thus, we define a rural-to-urban migrant as someone who currently lives in an urban area but maintains a rural *hukou*. Accordingly, a non-migrant (rural) child is someone who possesses a rural *hukou* and lives in the same county as that at birth, and whose current place of residence is classified as rural. A left-behind child is a non-migrant living in a rural area with at least one parent who has migrated to an urban residence.

Informed by previous research, we incorporate important individual, family, and county-level socioeconomic and demographic characteristics as matching variables in our PSM analysis. We control for children's demographic characteristics such as age and gender. We approximate family's socioeconomic status by parents' years of schooling. We do not include household income or parents' occupations since they are likely to be contaminated by the event of migration. Instead, we draw upon two dichotomous variables that capture family's socioeconomic status during early childhood – that is, indicators of whether or not a child was born in a hospital or clinic (versus at home or in some other non-clinic setting) and of whether a child ever attended a kindergarten, an uncommon life experience in rural China.

We capture family structure by incorporating dichotomous indicators of whether or not a child has at least one brother or sister and one living paternal or maternal grandparent(s). We further control for broader social and environmental factors that may affect the propensity for migration, including the percentage of agricultural population (and its squared term) and geographic region in a child's county of birth.

Analytical Sample

Among 3,464 children aged 10–15 sampled in the CFPS, 467 were urban natives, and 2,531 were rural-origin children of primary interest in this study (i.e., non-migrant, left-behind, and rural-to-urban migrant), with the rest consisting of other types of migrants (i.e., rural-to-rural, urban-to-urban, and urban-to-rural migrants). We excluded 77 rural-origin children (out of 2,531) because of missing information on their parental migration status, and 15 rural-to-urban migrant children (out of 224) who migrated without their parents. To remove ambiguity in parental migration status, we excluded 22 left-behind children (out of 423) whose parents did not move out of the same county and could maintain frequent (e.g., weekly or monthly) in-person interaction with their children. As a result, our sample prior to matching consists of 2,417 rural-origin children and 467 urban native children.

In our analytical sample, we drop 15% of the cases with missing data on any covariate. Preliminary analysis revealed little significant difference in the outcomes between the cases with and without missing covariates. Descriptive statistics of covariates can be found in Appendix Table A1. We choose not to impute the missing data because given the complex PSM and bootstrapping procedures, it is unclear how to obtain valid statistical inference (i.e., averaging the point estimates and estimating the standard errors) after imputation.

STATISTICAL MODEL

We apply PSM methods to estimate the so-called average treatment effects for the treated (ATT), that is, the average migration effects for the children who migrated or whose parents migrated. Borrowing the notation from the statistical framework of potential outcomes, let Y_i^T be the outcome for child i if he/she is treated (i.e. left-behind with migrant parents for the first causal question and being a migrant child for the second causal question), and let Y_i^C be the outcome for the same child if he/she is untreated (i.e. living in a non-migrant family). The ATT can be computed as:

$$\mathrm{ATT}=\mathrm{E}(\mathrm{Y}_i^T - \mathrm{Y}_i^C|\mathrm{D}_i=1)=\mathrm{E}(\mathrm{Y}_i^T|\mathrm{D}_i=1) - \mathrm{E}(\mathrm{Y}_1^C|\mathrm{D}_1=1)$$

where D =1 if being treated and 0 otherwise. However, it is impossible to observe Y_i^C for the same child who is treated. The underlying causal question here is what child i's wellbeing would be if he/she were to receive the treatment (i.e., migration), compared with not receiving the treatment (i.e., staying in rural areas). As only one of the two outcome values, Y_i^T or Y_i^C, is actually observed, we can only infer the treatment effect at the group rather than individual level under some assumption (Holland 1986). To infer ATT, we make use of an assumption that does not necessarily hold in reality; that is, the treated and untreated children are not systematically different in unobserved characteristics if they are matched on observable characteristics that affect treatment (Rosenbaum and Rubin 1983). In other words, if we assume that conditional on a set of observed characteristics, X, there exists a matched analogue in the control group for each treated child, then the following conditional independence is satisfied:

$$\mathrm{E}(\mathrm{Y}_i^C|\mathrm{X},\mathrm{D}_i=1)=\mathrm{E}(\mathrm{Y}_i^C|\mathrm{X},\mathrm{D}_i=0)=\mathrm{E}(\mathrm{Y}_1^C|\mathrm{X})$$

We can then estimate ATT as:

$$\mathrm{ATT}=\mathrm{E}[\mathrm{Y}^T|\mathrm{D}=1,\mathrm{Pr}(\mathrm{D}=1|\mathrm{X})] - \mathrm{E}[\mathrm{Y}^C|\mathrm{D}=0,\mathrm{Pr}(\mathrm{D}=1|\mathrm{X})]$$

where Pr(D=1|X) is the probability of being treated conditional on X. To estimate the effects of parental migration on child's wellbeing (i.e. the first causal question), we match the left-behind children with non-migrant children on a number of individual, family, and county-level socioeconomic and demographic variables. To answer the second causal question, we match the migrant children with non-migrants by their propensity score of migration on the same set of control variables.

Given the traditional son preference (Xie and Zhu 2009) and the vast gender difference in growth trajectories among Chinese children (Short, Xu and Liu 2013), we further perform exact matching on gender and apply PSM on the other control variables using the user-written Stata package *psmatch2* (Leuven and Sianesi 2003).[1] We restrict the matched sample to a region of common support, that is, only the matched cases with positive density of propensity scores within both the treatment and control distributions. In practice, a certain threshold value, known as a "trimming level," has to be employed to ensure that the densities of propensity score distribution are strictly positive. To ensure the robustness of PSM results, we explored different matching methods, including caliper matching, interval matching, kernel matching, and local linear matching (Smith and Todd 2005), and assessed the range of the estimates from the different methods. We present results from local linear matching given its relative efficiency.[2] Due to the technical complication of calculating standard errors in kernel-based nonparametric matching, we followed the conventional practice of bootstrapping standard errors from 2,000 iterations (Guo and Fraser 2010). In each iteration, we bootstrapped the entire two-stage procedure of first estimating propensity scores at the unit record level and then computing the average causal effect in terms of ATT. Abadie and Imbens (2008) suggest that bootstrap may provide valid inference for kernel-based matching estimators as used here, but not for simple matching estimators with a small number of matches such as nearest-neighbor matching. Nevertheless, certain caution should be exercised in interpreting our results.

We conducted Rosenbaum bounds sensitivity analysis for the estimation of ATT (Windmeijer 1990) using the user-written Stata package *rbounds* (DiPrete and Gangl 2004). In essence, this method involves a Wilcoxon signed rank test to evaluate how robust the estimated ATT is against the so-called hidden bias – a potential unobserved confounding variable that affects selection into the treatment group. Assuming certain level of potential impact of an unobserved confounding variable, we calculated a hypothetical significance level ("*p*-critical") of the estimated ATT. We varied the strength of the unobserved confounder, expressed in terms of the odds ratio of differential treatment assignment due to this omitted variable and denoted by Γ, to discern the extent to which the estimated ATT is biased (DiPrete and Gangl 2004).

[1]We have also estimated OLS regression models and obtained qualitatively similar results. We choose to present the results from PSM methods not only because they help reduce statistical bias by creating balanced comparison groups, but also because they are simpler and more natural as we focus on binary counterfactual comparisons.

[2]We used the default setting with Epanechnikov kernel function and the rule-of-thumb bandwidth.

RESULTS

Descriptive Statistics of the Dependent Variables

We begin by briefly describing the distributions of the dependent variables as reported in Table 3. On average, the rural-origin children passed about two thirds of the word test items and nearly half of the math test items, and achieved a letter grade between B and C in both Chinese language and math classes. About half of them were aware of who the top political leaders in China were, but only one third of them knew who the president of the U.S. was. The rural-origin children rarely reported depression symptoms and tended to maintain a relatively positive self-perspective. They had engaged in less than one quarrel with their parents in the last month and maintained more than 6 close friends on average.

They actively participated in housework (nearly three days per week) and spent a large amount of time (about 44 hours per week) on academic activities. They were slightly underweight in that their average body mass index (kg/m^2) was only about 17.6, although they ate a moderately diverse diet. In general, the interviewers held positive views regarding the rural-origin children's intelligence, language skills, and interactions with parents.

Effects of Parental Migration

We infer the effects of parental migration by comparing the left-behind against non-migrant children. We fit separate probit models for boys and girls to estimate their propensity scores for being left-behind by using the matching variables at individual, household, and county levels as described in the data section (also refer to Table 5). To conserve space, we do not present the model fitting results for the propensity score of parental migration. The estimates of ATT after matching are reported in Table 4. Surprisingly, the left-behind children were neither better- nor worse-off than those living in non-migrant families in nearly every aspect of their lives. The left-behind children did not seem to benefit from potentially increased economic resources from their parents' migration, which, in turn, might contribute to greater educational achievements, or better nutrition intakes or physical growth; nor did they suffer psychologically from the absence of their parents. In fact, the left-behind children spent on average 1.75 more hours per week doing homework compared to non-migrant children. Nevertheless, this effect was only marginally significant. These two groups of children were also viewed in similar ways by the interviewers in terms of cognitive and language skills as well as attention from parents (or guardians). In light of the minimal difference between the left-behind and the non-migrant children, we proceed to combine the left-behind and the non-migrant children into a single control group to infer the effects of migration on those who have migrated with their parents.

Effect of Child Migration

Before describing the main results on the effect of child migration, there are some findings from performing PSM worth notice. Table 5 reports coefficient estimates from probit models, stratified by gender for exact matching, of the propensity to be a migrant child. Overall, the model fits boys better than girls. However, the Hosmer-Lemeshow tests (Leuven and Sianesi 2003) which compared predicted probabilities with the observed data rejected the null of good fit to the data for boys ($p = 0.022$) but not for girls ($p = 0.190$).

Nevertheless, the Hosmer-Lemeshow test is known to be sensitive to the number of subgroups chosen *a prior*. In fact, when we varied the number of subgroups from the conventional standard of 10 to 9 or 11, the Hosmer-Lemeshow test failed to reject the null for boys. We further calculated the Pearson-Windmeijer goodness-of-fit test (Hosmer and Lemeshow 1980), which did not reject the null for boys ($p = 0.471$).

For both boys and girls, having attended kindergarten was associated with a higher probability of migration. Being born in a hospital instead of at home or in some other non-clinic setting was also positively related to the likelihood of migration for girls. Significant regional variations in the chance of migration also existed for both boys and girls. Father's education and having at least a brother were positively related to migration for boys but not girls. Living in a less urbanized county, as indicated by a larger percentage of agricultural population, was associated with a reduced likelihood of migration, and the strength of this relation was even greater as the degree of urbanization decreased. Overall, covariate balance has been improved after matching since most of the differences between the treated and control groups prior to matching have lost their significance (see Appendix Table A2). Even though there appears to be some imbalances in terms of region of birth after matching (central region for girls, and northern and southwestern regions for boys), these differences are only marginally or close to marginally significant ($p = 0.048$). Nevertheless, the results should be interpreted with caution.

Table 6 presents the estimates of ATT for child migration after matching. The migrant children scored significantly higher in the math test compared to the left-behind and non-migrant children. The migrant children had worse subjective wellbeing (i.e., more depressive and less positive self-perspective) and worse relationship with parents, but they also had more good friends. However, none of these effects is statistically significant. As for patterns of time use, the migrant children undertook housework more frequently and meanwhile spent more hours studying. They also enjoyed better nutrition-related outcomes in that they grew taller, gained more weight, and ate a more diversified diet. The improved wellbeing from migration was also confirmed by the interviewers' assessment. The migrant children were positively viewed as being more intelligent, having better language skills, and receiving more parental attention to their education, compared to the left-behind and non-migrant children.

For each of these significant effects, we assess its robustness against hidden bias by calculating hypothetical significance levels "*p*-critical" for a set of Γ (i.e., the odds ratio of differential treatment assignment due to an unobserved covariate) ranging from 1 to 2. The results are presented in Appendix Table A3. Some effects of migration are highly robust, whereas others are less so. For example, the *p*-critical associated with math test score is 0.065 (i.e., marginally significant) at $\Gamma = 1.1$ and 0.157 (i.e., insignificant) at $\Gamma = 1.2$. In other words, we would have to question the significant effect on math test score if an unobserved covariate caused the odds ratio of treatment assignment to differ between treatment and control cases by a factor of about 1.1 or 1.2. In contrast, the significance level of time spent studying is retained at $\Gamma = 2$ (p-critical = 0.011), indicating a highly robust effect.

Comparisons between Migrant and Urban Native Children

In order to further highlight the significant role of migration in shaping child development and provide new evidence on the debate between Scenarios 1 and 2 (see Figure 1), we compare the migrant children against their urban native peers, a common comparison in the literature, by mechanically matching the two groups on the same set of control variables as above without attempting any causal effect (see Table 7). Surprisingly, the migrant children were doing fairly well compared to their urban native peers, as they did not differ in most of the outcomes. The only advantage maintained by the urban native children was more time allocated to academic work. In fact, they had more depressive symptoms and ate a less diverse diet compared to that of the migrant children, although the latter may be contaminated by counting possibly unhealthy pickled or fried foods. Interviewer's observation also revealed surprisingly better language skill among the migrant children. This may be attributed to the highly selective nature of the migrant children, or may be indicative of differential reporting behaviors. Without further data, however, we are not able to adjudicate between these alternative explanations.

DISCUSSION

Rural-to-urban migration has been phenomenal and a driving force behind the rapid urbanization and economic boom in contemporary China and is likely to remain so in the near future. It is a complex demographic process that not only presents new life opportunities but also poses great challenges to the more than 262 million rural migrants currently working in urban China (National Bureau of Statistics of China 2013). More importantly, it inevitably affects the lives of migrants' children, regardless of whether they are brought to cities or left behind in the countryside. Grounded in the origin-destination framework (Landale and Oropesa 2001; Singley and Landale 1998), this study capitalizes on the new nationally representative CFPS data and draws a more balanced and holistic picture of internal migration processes and their consequences for rural-origin children.

Despite all sorts of social, environmental, and institutional barriers for rural-origin children migrating to and striving for a new life in urban China, we found these children to be better off compared to their peers remaining in the countryside. Migrant children achieved higher academic outcomes, possessed better language skills, enjoyed greater physical growth; meanwhile, they were not psychologically disturbed in the face of adapting to a more or less unfamiliar, and sometimes intimidating urban environment. We found that compared to their urban native peers, migrant children do fairly well across multiple life domains. This finding is consistent with two previous studies in the U.S. and China (Hirschman 2001; Liang, Guo and Duan 2008) reporting that migration children resembled their native-born peers at destination in educational outcomes. This is an encouraging finding as it highlights a potentially significant role of migration in narrowing the long-standing rural-urban gaps in child development in China. However, rural-to-urban migration remains a highly selective process. Only about 10 percent of the children in our sample were brought to cities by their migrant parents. Our models of propensity for child migration are merely satisfactory due to the limited amount of pre-migration information available. Therefore, our PSM analysis runs the risk of omitting variables that affect both the probability of migration and child wellbeing and consequently overestimating the positive effect of migration. Nevertheless, the positive effect of migration on children's objective wellbeing is consistent with our theoretical expectation.

We found little or no effect of parental migration on non-migrant children's wellbeing across a wide range of outcomes. This finding runs counter to our hypotheses and the conventional wisdom in the literature that presumes negative consequences to rural-origin children who are left behind (e.g., Huang 2004; Xiang 2007). It is possible that other adult family members step in after the parents have migrated. In fact, less than 30 percent of the left-behind children in our sample had both of their parents working in cities. That is, the majority of them were still living with one non-migrant parent, most often the mother (about 60 percent), who could still provide an arguably decent amount of parenting and caring. In addition, the prevalence of multigenerational coresidence in rural China enables grandparents to be natural surrogates for absent parents who have migrated (Zeng and Xie 2011). A few studies that draw on non-representative regional samples in rural China find no significant negative effect of parental migration on the left-behind children's school performance or educational attainment (Chen et al. 2009; Meyerhoefer and Chen 2011).

On the other hand, the finding that the left-behind children did not get ahead of non-migrant children in objective wellbeing suggests that the extra economic resources brought back by their migrant parents do not automatically transfer into gains in academic performance or nutrition. Instead, the effect of economic resources is likely to be contingent upon other factors such as parenting behavior, school quality, and neighborhood environment. In particular, increased household income is unlikely to induce sudden behavior changes among children, which, in turn, affect their wellbeing. For example, we did not find a significant difference in the amount of time spent studying, which helps to explain the minimal difference between the left-behind and non-migrant children in educational achievement. Similarly, the left-behind children may not benefit nutrition-wise from the remittance sent back by their migrant parents as long as the local food environment remains poor. Our findings of the significant positive effects of child migration on test score, time spent studying, and nutrition-related outcomes suggest that the impact of economic resources may hinge on migrant children's own exposure to urban environments, an empowering experience that not only involves greater structural opportunities but also boosts their aspirations for success.

This study is limited in several ways. Most measures of the dependent and independent variables are collected through either self- or proxy-reports by parents and are hence subject to reporting errors. The fact that the CFPS data are of high quality in a number of key socioeconomic and demographic variables as suggested in our preliminary analysis (Xie 2012) by no means assures the same level of quality in other measures, especially those susceptible to issues of sensitivity and social desirability, including proxy-reported schooling grades, and self-reported mental health, body weight and height, and time use. We address this issue by drawing upon the supplementary data collected from interviewers' observations which prove to have high accuracy rates with respect to family relationship and respondent's behavior outcomes (West 2013), but admittedly, we are limited in our capacity to fully address the measurement errors. Nevertheless, some studies of Chinese children have suggested high correlations (above 0.9) between self-reported and measured body weight and height (Zhou et al. 2010), high correlations (above 0.7) between proxy- and self-reported mental health and social behaviors (Du, Kou and Coghill 2008), and reliable self-reports of time use patterns (Tudor-Locke et al. 2003). Using the CFPS data from a single wave in this paper, we are restricted to the amount of accurate information prior to migration to improve the estimation of propensity score, especially for girls. We are also limited in our ability to examine the effect of migration on changes in children's wellbeing over time. Fortunately, it will not be long before new waves of the CFPS data become available to permit us to address these challenges.

These limitations do not necessarily undermine the strengths of this study. We are among the first to infer the effect of migration on rural-origin children from a counterfactual perspective. Applying PSM techniques, we construct more comparable subsamples for estimating the effects of migration. By capturing rural-origin children living in different locations, we make fine-grained comparisons across three distinct groups – children living with non-migrant parents in the countryside, children of migrant parents who have been left behind at rural places of origin, and rural-origin children who have migrated to cities with their migrant parents. We thus expand the existing origin-destination approach (Landale and Oropesa 2001; Singley and Landale 1998) that focuses on only the migrants and non-migrants in studying the effects of migration. The representativeness of our sample allows us to generalize our findings to the child population in China. Future research is needed to understand the effect of migration on changes in children's wellbeing and to disentangle the specific mechanisms at work.

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APPENDIX

Table A1

Descriptive statistics of matching covariates.

	Girls		Boys	
	Mean or %	**SD**	**Mean or %**	**SD**
Age (years)	12.56	1.74	12.57	1.71

	Girls		Boys	
	Mean or %	SD	Mean or %	SD
Father's education (years)	6.94	4.32	6.95	4.16
Mother's education (years)	5.32	4.64	5.16	4.42
Had brother(s) (%)	58.63	—	33.28	—
Had sister(s) (%)	40.11	—	45.23	—
Paternal grandparent(s) alive (%)	86.03	—	86.91	—
Maternal grandparent(s) alive (%)	90.66	—	88.93	—
Born in a hospital (%)	46.78	—	50.00	—
Ever attended kindergarten (%)	56.75	—	59.77	—
% Agricultural population in the county	0.72	0.27	0.72	0.27
Place of birth (%)				
North	10.68	—	9.69	—
Northeast	9.73	—	9.77	—
East	10.36	—	11.39	—
Central	18.60	—	19.39	—
South	16.17	—	16.64	—
Southwest	14.68	—	16.32	—
Northwest	19.78	—	16.80	—
N prior to matching	1,274		1,238	

Table A2

Covariate balance in estimating the average treatment effect of child migration on the word test score.

		Girls (Mean)		Boys (Mean)	
		Treated	Control	Treated	Control
Age (years)	Unmatched	12.24	12.56 †	12.44	12.60
	Matched	12.25	12.33	12.42	12.27
Father’s education (years)	Unmatched	7.17	6.16 *	7.73	6.23 ***
	Matched	7.16	7.29	7.71	6.80
Mother’s education (years)	Unmatched	5.85	4.29 ***	5.80	4.23 ***
	Matched	5.85	5.00	5.77	4.70 †
Had brother(s)	Unmatched	0.63	0.66	0.36	0.36
	Matched	0.62	0.67	0.36	0.42
Had sister(s)	Unmatched	0.36	0.45 †	0.40	0.51 *
	Matched	0.35	0.32	0.40	0.40
Paternal grandparent(s) alive	Unmatched	0.81	0.86	0.90	0.86
	Matched	0.83	0.88	0.90	0.93

		Girls (Mean)		Boys (Mean)	
		Treated	Control	Treated	Control
Paternal grandparent(s) alive	Unmatched	0.93	0.91	0.93	0.88
	Matched	0.92	0.91	0.93	0.92
Born in a hospital	Unmatched	0.58	0.38 ***	0.64	0.41 ***
	Matched	0.57	0.58	0.63	0.60
Ever attended a kindergarten	Unmatched	0.82	0.48 ***	0.84	0.51 ***
	Matched	0.82	0.76	0.83	0.80
% Agricultural population (county)	Unmatched	0.74	0.79 *	0.70	0.79 ***
	Matched	0.76	0.73	0.71	0.77
% Agricultural population squared	Unmatched	0.60	0.66 *	0.57	0.66 **
	Matched	0.62	0.60	0.57	0.65 †
Region of Birth (ref: East)					
North	Unmatched	0.13	0.11	0.09	0.11
	Matched	0.13	0.12	0.09	0.02 †
Northeast	Unmatched	0.09	0.08	0.05	0.08
	Matched	0.10	0.05	0.06	0.03
Central	Unmatched	0.14	0.17	0.16	0.18
	Matched	0.14	0.05 *	0.17	0.17
South	Unmatched	0.21	0.16	0.20	0.16
	Matched	0.19	0.23	0.19	0.16
Southwest	Unmatched	0.21	0.16	0.19	0.18
	Matched	0.22	0.29	0.19	0.31 †
Northwest	Unmatched	0.12	0.23 **	0.10	0.20 *
	Matched	0.12	0.13	0.10	0.11

Note: The control group include non-migrant and left-behind children.

† $p < .1$;

* $p < .05$;

** $p < .01$;

*** $p < .001$ (two-tailed tests).

Table A3

Rosenbuam bounds sensitivity analysis of child migration treatment effects.

	Γ										
	1.0	**1.1**	**1.2**	**1.3**	**1.4**	**1.5**	**1.6**	**1.7**	**1.8**	**1.9**	**2.0**
Educational performance (*p*-critical)											
Math test score	0.019	0.065	0.157	0.293	0.454	0.611	0.744	0.843	0.910	0.951	0.975

	Γ										
	1.0	**1.1**	**1.2**	**1.3**	**1.4**	**1.5**	**1.6**	**1.7**	**1.8**	**1.9**	**2.0**
Time Use (*p*-critical)											
Days/week doing housework/farming	0.001	0.007	0.026	0.069	0.144	0.253	0.383	0.519	0.646	0.753	0.835
Hours/week studying	<.001	<.001	<.001	<.001	<.001	<.001	<.001	0.001	0.002	0.005	0.011
Health & Nutrition (*p*-critical)											
Height (cm)	0.025	0.081	0.184	0.329	0.493	0.647	0.772	0.863	0.923	0.959	0.979
Weight (kg)	0.152	0.317	0.511	0.688	0.821	0.906	0.955	0.980	0.991	0.997	0.999
N of food types eaten last month	<.001	<.001	0.001	0.003	0.010	0.027	0.058	0.109	0.180	0.269	0.369
Interviewer’s observation (*p*-critical)											
Comprehension capability	0.010	0.039	0.104	0.215	0.359	0.516	0.661	0.778	0.864	0.921	0.957
Mandarin fluency	<.001	<.001	<.001	<.001	<.001	0.001	0.003	0.008	0.018	0.036	0.063
Intelligence	<.001	0.001	0.001	0.013	0.035	0.078	0.146	0.238	0.347	0.464	0.578
Self-expression	<.001	<.001	<.001	0.001	0.004	0.012	0.029	0.058	0.105	0.169	0.249
Parents care child's education	<.001	<.001	<.001	<.001	0.001	0.004	0.012	0.026	0.052	0.091	0.145

Note: Rural-to-urban migrant children are the treated group, whereas left-behind and non-migrant children are the control. The *p*-critical represents the bound on the significance level of the treatment effect while setting the level of hidden bias (differential selection into treatment due to an unobserved covariate) to a certain value Γ.

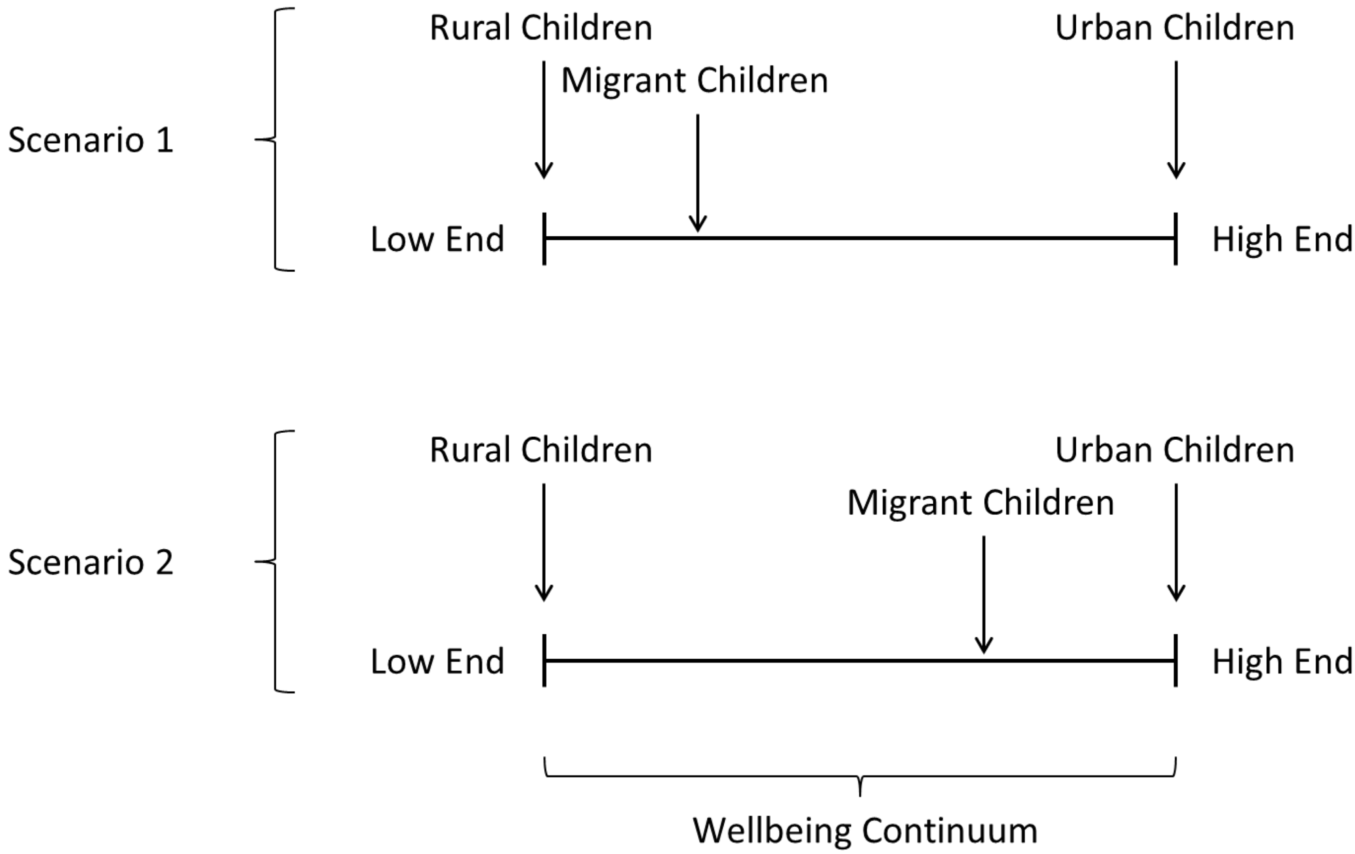

Figure 1.
Visualization of two scenarios of the effect of migration on Chinese children's wellbeing.

Table 1

Typology of rural-origin children (10–15 years): CFPS 2010

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="3">Parental Migration Status</td></tr>
<tr><td>No</td><td colspan="2">Yes</td></tr>
<tr><td rowspan="3">Rural Child’s
Migration Status
(N = 2,454)</td><td rowspan="2">No</td><td rowspan="2">A: Non-migrant
(N = 1,807; 73.6%)</td><td colspan="2">B: Left-behind
(N = 423; 17.2%)</td></tr>
<tr><td>B1: Within County
(N = 22; 0.9%)</td><td>B2: Across County
(N = 401; 16.3%)</td></tr>
<tr><td>Yes</td><td>D: Migrant without Parent(s)
(N = 15; 0.6%)</td><td colspan="2">C: Migrant with Parent(s)
(N = 209; 8.5%)</td></tr>
</table>

Note: N refers to the sample size prior to propensity score matching. The analytical sample is restricted to subgroups A, B2, and C with a total number of 2,417 children.

Table 2

Conceptual comparisons among three types of rural-origin children.

	Non-Migrant	Left-Behind	Migrant
Parental migration	No	Yes	Yes
Economic resource	−	+	+
Self-migration	No	No	Yes
Exposure to urban environment	−/+	−/+	+/−
Co-residence with parent(s)	Yes	No (or partial)	Yes
Parenting	+	−	+

Table 3

Definitions and descriptive statistics of the dependent variables in the analytical sample of rural-origin children (10–15 years; N = 2,112): CFPS 2010

Dependent Variable	Definition	Mean	SD	N (% Missing)
Educational Performance				
Word test score	34-item Chinese word test	21.17	7.24	2,044 (3.2%)
Math test score	24-item mathematical test	10.87	4.50	2,044 (3.2%)
Chinese grade	Parent-reported 4-scale grade in the last semester	2.60	0.94	2,012 (4.7%)
Math grade	Parent-reported 4-scale grade in the last semester	2.54	1.00	2,013 (4.7%)
Political Knowledge	Factor analysis score of 3 items about political leaders	−0.11	0.97	2,008 (4.9%)
Subjective Well-Being				
Depression	Factor analysis score of 6-item CES-D	−0.03	0.97	2,086 (1.2%)
Positive self-perspective	Factor analysis score of 4 Likert-type items (popularity/happiness/self-confidence/easygoing)	−0.03	0.99	2,096 (0.8%)
Inter-Person Relationship				
N of quarrels with parents last month	Frequency in the last month	0.45	1.73	2,098 (0.7%)
N of good friends	Self-enumerated	6.06	8.13	2,109 (0.1%)
Time Use				
Days per week doing housework/farming	Frequency of participation	2.69	2.38	2,104 (0.4%)
Hours per week studying	Duration of time	43.83	17.65	2,112 (0.0%)
Nutrition				
Height	In centimeters	146.52	15.17	1,993 (5.6%)
Weight	In kilograms	37.61	10.82	1,988 (5.9%)
N of food types eaten last month	Meat, fish, vegetable, dairy product, bean, egg, pickled food, and fried food	4.45	1.99	2,112 (0.0%)
Interviewer’s Observation				
Comprehension capability	7-point Likert scale	4.99	1.26	2,107 (0.2%)
Mandarin fluency	7-point Likert scale	4.44	1.61	2,107 (0.2%)
Intelligence	7-point Likert scale	5.04	1.17	2,107 (0.2%)
Self-expression	7-point Likert scale	5.05	1.23	2,107 (0.2%)
Parents care child's education	5-point Likert scale	3.28	0.73	2,112 (0.0%)
Parents actively communicate with child	5-point Likert scale	3.47	0.69	2,112 (0.0%)

Table 4

Estimates of the average treatment effects on the treated (left-behind children) with non-migrant children as the control group.

	Left-behind		Non-migrant			
	Mean	**N**	**Mean**	**N**	**ATT**	**SE**
Educational Performance						
Word test score	20.68	258	20.83	1600	−0.15	(0.44)
Math test score	10.19	258	10.56	1600	−0.37	(0.26)
Parent-reported Chinese grade	2.53	254	2.54	1575	−0.01	(0.07)
Parent-reported Math grade	2.51	254	2.47	1575	0.05	(0.07)
Political Knowledge	−0.24	241	−0.18	1585	−0.06	(0.06)
Subjective Wellbeing						
Depression	0.09	256	−0.01	1642	0.10	(0.08)
Positive self-perspective	0.00	256	−0.06	1652	0.06	(0.07)
Inter-person Relationship						
N of quarrels with parents last month	0.33	260	0.47	1650	−0.14	(0.10)
N of good friends	5.12	258	5.85	1662	−0.73	(0.47)
Time Use						
Days/week doing housework/farming	2.75	260	2.89	1656	−0.14	(0.16)
Hours/week studying	44.67	260	42.92	1663	$1.75^{\dagger}$	(1.06)
Health & Nutrition						
Height (cm)	145.74	241	145.08	1569	0.66	(0.83)
Weight (kg)	36.17	242	36.12	1565	0.05	(0.58)
N of food types eaten last month	4.28	260	4.27	1663	0.01	(0.13)
Interviewer’s Observation						
Comprehension capability	5.00	260	4.93	1658	0.06	(0.09)
Mandarin fluency	4.37	260	4.34	1658	0.04	(0.11)
Intelligence	4.99	260	4.99	1658	−0.01	(0.09)
Self-expression	5.00	260	4.95	1658	0.05	(0.09)
Parents care child's education	3.18	260	3.25	1663	−0.07	(0.05)
Parents actively communicate with child	3.44	260	3.42	1663	0.02	(0.05)

Note: SE = Bootstrap standard errors with 2,000 iterations; ATT = average treatment effects on the treated; N refers to the number of matched cases.

† $p < .1$;

* $p < .05$;

** $p < .01$;

*** $p < .001$ (two-tailed tests).

Table 5

Estimates of propensity for rural-to-urban migration experienced by children

	Girls		Boys	
	β	SE	β	SE
Age (years)	−0.01	(0.04)	−0.02	(0.04)
Father's years of education	0.01	(0.02)	0.03†	(0.02)
Mother's years of education	0.02	(0.02)	0.02	(0.02)
Had brother(s) (ref = No)	0.07	(0.15)	0.26†	(0.15)
Had sister(s) (ref = No)	−0.09	(0.13)	0.00	(0.14)
Paternal grandparent(s) alive (ref = No)	−0.26	(0.16)	0.17	(0.20)
Maternal grandparent(s) alive (ref = No)	0.07	(0.22)	0.17	(0.22)
Born in a hospital(ref = no)	0.27*	(0.13)	0.19	(0.14)
Ever attended kindergarten (ref = no)	0.74***	(0.15)	0.72***	(0.15)
% Agricultural population (county of birth)	−0.94	(1.17)	−3.16**	(1.12)
% Agricultural population squared	0.67	(1.09)	2.57*	(1.08)
Place of birth (ref = East)				
North	0.09	(0.26)	−0.49†	(0.26)
Northeast	0.20	(0.27)	−0.55*	(0.28)
Central	0.02	(0.25)	−0.35	(0.23)
South	0.36	(0.25)	−0.20	(0.23)
Southwest	0.62*	(0.25)	0.06	(0.23)
Northwest	0.21	(0.26)	−0.32	(0.24)
Constant	−1.74**	(0.67)	−1.36*	(0.68)
N	1,031		1,013	

Note: SE = standard errors.

† $p < .1$;

* $p < .05$;

** $p < .01$;

*** $p < .001$ (two-tailed tests).

Table 6

Estimates of the average treatment effects on the treated (migrant children) with non-migrant and left-behind children as the control group.

	Migrant		Non-migrant & Left-behind			
	Mean	**N**	**Mean**	**N**	**ATT**	**SE**
Educational Performance						
Word test score	22.04	183	21.34	1,858	0.70	(0.49)
Math test score	11.17	183	10.61	1,858	0.56^{*}	(0.28)
Parent-reported Chinese grade	2.76	179	2.74	1,829	0.02	(0.08)
Parent-reported Math grade	2.61	180	2.65	1,829	−0.04	(0.09)
Political Knowledge	0.03	178	−0.09	1,826	0.12	(0.08)
Subjective Wellbeing						
Depression	−0.04	185	−0.06	1,898	0.02	(0.08)
Positive self-perspective	0.00	185	0.03	1,908	−0.03	(0.09)
Inter-person Relationship						
N of quarrels with parents last month	0.65	185	0.56	1,910	0.09	(0.20)
N of good friends	7.47	186	6.46	1,920	1.00	(0.74)
Time Use						
Days/week doing housework/farming	3.25	185	2.49	1,916	0.77^{***}	(0.20)
Hours/week studying	48.92	186	43.98	1,923	4.94^{***}	(1.19)
Health & Nutrition						
Height (cm)	147.82	179	145.81	1,810	$2.00^{\dagger}$	(1.03)
Weight (kg)	38.69	179	37.33	1,807	$1.36^{\dagger}$	(0.79)
N of food types eaten last month	5.43	186	4.85	1,923	0.58^{***}	(0.14)
Interviewer's Observation						
Comprehension capability	5.33	186	5.14	1,918	0.19^{*}	(0.09)
Mandarin fluency	5.15	186	4.66	1,918	0.49^{***}	(0.10)
Intelligence	5.45	186	5.13	1,918	0.32^{***}	(0.09)
Self-expression	5.51	186	5.20	1,918	0.31^{***}	(0.09)
Parents care child's education	3.50	186	3.35	1,923	0.15^{**}	(0.05)

	Migrant		Non-migrant & Left-behind			
	Mean	**N**	**Mean**	**N**	**ATT**	**SE**
Parents actively communicate with child	3.55	186	3.54	1,923	0.02	(0.05)

Note: SE = Bootstrap standard errors with 2,000 iterations; ATT = average treatment effects on the treated; N refers to the number of matched cases.

† $p < .1$;

* $p < .05$;

** $p < .01$;

*** $p < .001$ (two-tailed tests).

Table 7

Mechanical estimates of the “average treatment effects on the treated” (migrant children) with urban native children as the control group.

	Migrant		Urban Native			
	Mean	**N**	**Mean**	**N**	**ATT**	
Educational Performance						
Word test score	22.89	152	22.90	382	−0.01	(1.00)
Math test score	11.74	152	12.28	382	−0.55	(0.49)
Parent-reported Chinese grade	2.85	149	2.70	379	0.15	(0.13)
Parent-reported Math grade	2.61	150	2.70	379	−0.10	(0.14)
Political Knowledge	0.11	149	0.06	381	0.04	(0.14)
Subjective Wellbeing						
Depression	−0.06	155	0.21	384	$-0.27^{\dagger}$	(0.15)
Positive self-perspective	0.05	154	−0.09	384	0.14	(0.14)
Inter-person Relationship						
N of quarrels with parents last month	0.68	154	0.83	384	−0.15	(0.35)
N of good friends	7.30	155	8.98	385	−1.68	(1.91)
Time Use						
Days/week doing housework/farming	3.14	154	2.91	385	0.23	(0.38)
Hours/week studying	48.75	155	52.81	385	$-4.06^{\dagger}$	(2.16)
Health & Nutrition						
Height (cm)	149.51	155	150.81	382	−1.30	(1.80)
Weight (kg)	39.98	149	40.42	382	−0.44	(1.31)
N of food types eaten last month	5.70	155	5.27	385	$0.42^{\dagger}$	(0.26)
Interviewer’s Observation						
Comprehension capability	5.45	155	5.33	385	0.12	(0.14)
Mandarin fluency	5.31	155	4.66	385	0.65^{**}	(0.21)
Intelligence	5.50	155	5.36	385	0.14	(0.15)
Self-expression	5.59	155	5.28	385	$0.32^{\dagger}$	(0.17)
Parents care child’s education	3.54	155	3.44	385	0.10	(0.10)
Parents actively communicate with child	3.62	155	3.60	385	0.02	(0.10)

Note: SE = Bootstrap standard errors with 2,000 iterations; ATT = average treatment effects on the treated; N refers to the number of matched cases.

†$p < .1$;

*$p < .05$;

**$p < .01$;

***$p < .001$ (two-tailed tests).