The Effect of Childhood Migration on Human Capital Accumulation: Evidence from Rural-Urban Migrants in Indonesia

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Abstract
Developing countries are experiencing unprecedented levels of urbanization. Although most of these movements are motivated by economic reasons, they could affect the human capital accumulation of the children who follow their parents to the cities. This paper estimates the causal effect of permanently migrating as a child from a rural area to an urban area on human capital outcomes. To our knowledge, this paper is one of only several papers, especially in the context of a developing country, which is able to estimate the causal effect of migration. We utilize a recent survey of urban-rural migrants in Indonesia and merge it with a nationally representative survey to create a dataset that contains migrants in urban areas and non-migrants in rural areas who were born in the same rural districts. We then employ a measure of district-level propensity to migrate, calculated from the Indonesian intercensal survey, as an instrument. We find that childhood migration to urban areas increase education attainment by about 4.5 years by the time these individuals are adults. In addition, the childhood migrants face a lower probability to be underweight by about 15 percentage points as adults. However, we find no statistically significant effect on height, which is a measure of long-term nutritional intake, and we only find a weak effect on the probability to be obese. Therefore, our results suggest a permanent, positive, and large effect of childhood migration on education attainment and some health measures. In addition, our results can rule out any negative effect on health.
I. Introduction

Urbanization continues to occur at increasingly faster rates in developing countries. In China, for example, the number of people from rural areas living in urban areas has tripled between 1997 and 2005, reaching as high as 126 million in 2005 (Frijters and Meng, 2009). The figure is even more astounding given the significant obstacle facing rural residents who migrated to urban areas caused by the household registration (hukou) system operating in the country. The urbanization rate in Indonesia, where rural residents are free to move to urban areas, is also astronomical. It had taken the country 40 years, from 1950 to 1990, to double the share of population living in urban areas from 15% to 30%. However, it only took a further 15 years for the share to reach 48% (Sarosa, 2006).

In most cases, migration is prompted by economic reasons. Whether motivated by relative or absolute gains, standard economic theory predicts that a person will migrate if the net benefit of migrating is larger than the net benefit of not migrating. Starting with that platform, our aim in this paper is to investigate the presence of externality in an economically motivated migration. Specifically, the externality that we examine is the effect of migration on the education and health of children of the migrants who followed their parents to the urban areas.

Conceptually, the channels through which migrating from a rural to an urban area positively affects the human capital of a child may be in the form of better access to health and education facilities in urban areas, an environment that is more supportive to human capital accumulation compared to the environment in rural areas, or a higher labor market returns to human capital in urban areas. Conversely, migration could have a negative effect on a child’s human capital accumulation. As an example, the child could actually have less access to these services compared to children in rural areas since the price of education or health services is generally higher in urban areas, or that there exists other barriers in accessing these services. As an example, children of migrants in China face a significant barrier in going to school as their parents are not registered as urban residents. Moreover, it may be the case that the child engages in market work as opposed to attending school, since the opportunity cost of schooling is higher in urban areas as there are more employment opportunities. The third mechanism that could result in a negative effect of migration on the child’s human capital, especially health, is through a dietary change or lower environmental quality in urban areas.

There are many studies that compare the education and health outcomes of migrant children with both children in destination and children in the origin (e.g. Kong and Meng, 2010; Stiefel, Schwartz, and Konger, 2010; Rubalcava et al, 2008; Liang and Chen, 2007; Gang and Zimmerman, 2000). However, the crucial aspect in this type of investigation pertains to the fact that migrants are not randomly drawn from the population. Therefore, the econometrician needs a valid instrument in order to identify the econometric model and estimate the causal effect of migration.  

1 Another method that has been employed is to exploit a lottery program in Tonga (Stillman, Gibson, and McKenzie, 2010).
Among studies that are able to identify the causal effect of migration, Stillman, Gibson, and McKenzie (2010) exploit a lottery program in Tonga, where the winners are allowed to migrate to New Zealand. They find that the children of Tongan migrants, who followed their parents, are more obese than observably similar children living in Tonga. In Mexico, McKenzie and Rapoport (2010) use historical migration network between Mexico and United States to measure the effect of having a migrant household member on the education attainment of children in Mexico. They find a large and negative effect on the probability of finishing junior high school for boys and on the probability to finish high school for girls.

In this paper, our migrant sample consists of Indonesian rural-urban migrants who were enumerated as a part of a study specifically designed to document the outcomes of migrants, the Rural-Urban Migration in China and Indonesia (RUMiCI) survey. RUMiCI contains rich and detailed information on the migrants, such as their occupation prior to migration, the specific date of their migration, the reasons for migrating, and the complete list of children or relatives who remained in rural areas. To our knowledge, there are only very few datasets in other developing countries with such information. Given our interest of estimating the effect of migration on people who migrated when they were children, we limit our sample to those who were between the age of five and 15 when they moved with their parents to the city. During the RUMiCI survey, the majority of these individuals are already adults. Therefore, we are estimating the long-term effect of migration. This is an additional contribution to the literature, as the studies in the previous paragraph focus on individuals between 0 and 18 years old.

For the instrument, we use the Indonesian intercensal survey to calculate the number of migrants from a particular rural district that have migrated to a particular urban city and then divide the number by the number of people still residing in the rural district. We think of the ratio as the propensity to migrate among residents of a rural district. We then estimate the effect of childhood migration on an individual’s final education attainment and current health conditions.

Our estimation results show that childhood migration to urban areas increased education attainment by about four more years of schooling relative to an observably similar individual who remained in the rural area. In addition, the childhood migrants are significantly healthier, facing a lower probability to be underweight by about fourteen percentage points. However, we find no statistically significant effect on height, which is a measure of long-term health. Comparing the two-stage least squares (2SLS) with the ordinary least squares (OLS) results, the OLS estimates appear to

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2 The Indonesian Family Life Survey (IFLS) also has a module on migration patterns. However, the information on a person’s district of residence when he or she was 12 years old, which we need for this paper, is missing in the two latest waves of the survey. Therefore, in the context of Indonesia, RUMiCI is the only dataset that contains the information that we need.

3 Boheim and Taylor (2007) use the age of youngest child as an instrument, with wage growth of the parent as the outcome variable. They also have access to a panel dataset that allows them to control for factors prior to the migration occurring.
underestimate the effect of migration with regards to education attainment and malnutrition, but overestimate the effect of migration on height and obesity.

We organize the rest of the paper as follows. The next section describes the datasets and sample construction in more detail. Section III describes rural-urban migration in the country. We then discuss our identification strategy and the estimation results in Section IV. In the penultimate channel, we investigate the potential channels through which migration affects an individual’s education and health outcomes. The final section concludes.

II. Data and Sample Construction

The two main datasets for this paper come from the rural-urban migration in China and Indonesia (RUMiCI) project conducted by the Australian National University and the national socio-economic survey (Susenas - Survei Sosio-Ekonomi Nasional) conducted by the Statistics Indonesia (or the Indonesian central statistical agency). RUMiCI is a household level survey conducted in China and Indonesia to investigate the labor market activities and welfare of individuals who have migrated from rural to urban areas. The specific population of interest in this survey are households whose heads have migrated from a rural to an urban area. In Indonesia, the survey is implemented in Medan, Tangerang\textsuperscript{4}, Samarinda and Makassar. These four cities represent the largest enclave areas in each of the four broad geographic Indonesian regions: (1) Sumatra, (2) Java and Bali, (3) Kalimantan and (4) Sulawesi, Papua, Maluku and Nusa Tenggara (that is, Eastern Indonesia). The total sample in Indonesia is approximately 2400 households, in which approximately 1500 of them are rural-urban migrant households. The questionnaire developed in this survey aims to gather rich information on migrant’s place of origin, educational attainment, poverty, health, and labor supply. This survey is an annual longitudinal survey conducted from 2008 to 2011 (Resosudarmo, Yamauchi and Effendi, 2010). Data utilized in this paper comes from the survey in 2008. To date, RUMiCI is the only survey specifically designed to understand rural-urban migrants in Indonesia.

Susenas is a large scale, nationally representative, repeated cross-section household level survey conducted since 1960s. The main aim of Susenas is to gather complete, accurate, and timely data on important characteristics of the population. Information collected includes those on place and living condition, educational attainment, poverty, health and labor supply. This paper utilizes only the rural households from the 2007 who live in the rural areas where the rural-urban migrant households in the RUMiCI come from.

Sample Construction

We construct the sample the following way. From the RUMiCI dataset, we keep individuals who were between five and 15 years old when they migrated to the city. Note that most of these

\textsuperscript{4}Tangerang, in this case, is chosen as a proxy for Jakarta.
individuals are already adults when they were enumerated in the RUMiCI survey. From the RUMiCI survey, 331 respondents fulfill this criterion. We then take Susenas and keep individuals currently living in the districts where the RUMiCI rural-urban migrants were born in, about 101,946 observations. Merging these two datasets gives us a dataset that contains migrants (from RUMiCI) and non-migrants (from Susenas) who were born in the same set of rural districts.\(^5\) We then remove districts that are only represented by one observation from the dataset.

Finally, we use the 2005 intercensal survey (Supas – survei penduduk antar sensus) to calculate our instrument, the ratio between the number of migrants from a rural district in a city and the number of population in the rural district. This ratio ranges from zero, implying that no one in the rural district lives in a particular city, and has no upper bound.

### III. Rural-Urban Migration in Indonesia

Statistics Indonesia, the government statistics agency, typically defines rural-urban migrants as those who were born in rural areas and are currently residing in an urban area. The 2005 Supas recorded that among urban residents, approximately 24.2% were migrants from rural areas. Hence, in any urban area in Indonesia, the density of rural-to-urban migrants is likely to be substantial. In the four cities where RUMiCI is conducted, the proportions of rural-to-urban migrant vary as well. As shown in Table 1, Medan has a lower share than the national average, while Tangerang is right at the national average. In contrast, Makassar and Tangerang have much higher share of rural-urban migrants in their population compared to the national average. Among the migrants in these four cities, between 12.6% and 16.7% of them are children.

[RANDOTABLE 1 HERE]

RUMiCI’s definition on rural-urban migrant is different than the definition employed by Statistics Indonesia. In RUMiCI, rural-urban migrants are those who had spent at least five years in rural areas before the age of 12 and are currently living in the city. Table 2 shows the living arrangements of children of the migrants. There is a total of 1,904 children with age less or equal than 16 year old or above 16 but still in school. Among these children, approximately 91% are living with their parents in the city, while approximately 5.5% are left behind in the rural area, and the rest live in the city but not with the main respondent household. The main reasons for leaving the children behind are high living cost in the city and lack of care for the child in the city. In the rural areas, most of the left-behind children stay with their grandparents. If we restrict the sample to children who were born in rural areas, we are left with 236 children. All of these children are currently living with their parents.

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\(^5\) This assumes that individuals currently living in a rural district were born there. This assumption is not strong, as migration from one rural district to another rural district is rare in Indonesia.
in the urban areas. Therefore, a stylized fact of rural-urban migrants in Indonesia is that they migrate as a family.

TABLE 2 HERE

IV. Human Capital Outcomes of Childhood Migrants Relative to Non-Migrants.

In this paper, we examine the human capital outcomes of childhood migrants relative to individuals who remain in the rural areas along four dimensions: years of schooling, height, obesity, and malnourishment. Specifically, obesity is defined as having a BMI of over 30, and malnourishment is defined as having a BMI of below 16.5.

Figure 1 shows the polynomial fit of these four outcomes by migration status and age. The top left figure shows that without controlling for any covariates, childhood migrants enjoy about 3 to 5 years more schooling than non-migrants. The gap is statistically significant across the whole age period. Interestingly, the gap appears to be relatively constant, implying that the benefit of migration to urban areas with regards to education attainment has remained relatively unchanged for the different cohorts of individuals.

FIGURE 1 HERE

The bottom left figure, meanwhile, shows that the gap in the probability to be underweight only occurs between the ages of 10 and 20, and then after 55 years. During both periods, non-migrants have a higher chance to be underweight. On the other hand, the slightly higher prevalence of malnourishment among migrants between the ages of 30 and 50 is not statistically significant. The second measure of health, obesity, provides a stark gap between migrants and non-migrants. However, none of the gap is statistically significant, except between the ages of 42 and 48. During these ages, migrants have about 5 percentage points higher probability to be obese. The final health outcome, height, measures long-term health. The bottom right figure shows that migrants are about 5 centimeters taller than non-migrants, and the gap is statistically significant for individuals older than 15 years old. Similar to education attainment, the gap appears to be relatively the same over individuals of different ages. In the next section, we discuss the identification strategy that allows us to measure the causal effect of childhood migration on these outcomes.

V. Identification Strategy and Estimation Results

The econometric model that we want to estimate is shown in Equation 1.

\[ Y_{ij} = \alpha + \beta_M M_{ij} + \beta_X X_{ij} + \varepsilon_{ij} \] (1)
where $Y_{ij}$ is the education and health outcomes of individual $i$ who were born in rural district $j$. In this paper, we use years of schooling, an indicator of obesity, an indicator of malnourishment, and height. Our main explanatory variable is $M_{ij}$, which is equal to one if the individual followed their parents to the city and currently live in the city, and is equal to zero if the individual have always lived in the rural district $j$. Finally, $X_{ij}$ is a vector of control variables, which contains individual variables such as age, current marital status, and sex; and current household size.

As we mention in the introduction, the main difficulty in measuring the causal effect of migration lies in the fact that migrants are not a randomly selected group from the population (McKenzie, Gibson, and Stillman, 2010). In addition, in countries like China, around half of the children of migrants are left behind in the rural areas (Kong and Meng, 2010). Therefore, the children who migrated with their parents to the city have gone through two selection processes. This implies that a least squares estimation of Equation 1 is likely to produce biased coefficients. One cannot consider $\beta_M$ as the causal effect of childhood migration on an individual’s current human capital outcomes.

The fact that the share of left-behind children is very low in the Indonesian case implies that in most cases, rural-urban migrants took their family along when they move to the city. This stylized fact reduces the estimation difficulty that we need to consider when we estimate the effect of childhood migration, as we only need to worry about one selection process rather than two processes.

**Instrument**

In order to identify the model, we use the propensity for migration of a rural district as the instrument. This is calculated by taking the number of migrants from a particular rural district that have migrated to a particular urban city—in our case, each of the four cities in RUMiCI—and then divide the number by the number of people currently still residing in the rural district. Since our instrument is calculated at the district level, our identification relies on the assumption that the variation in the propensity to migrate across districts is not correlated with the variation in a child’s eventual education and health outcomes. In addition, we include additional controls to our model, such as island of birth fixed effects, to make sure that the districts that we compare from are comparatively similar. In addition, we control for remoteness and access to health and education facilities at the village where the residents were born in. Finally, we include a measure of education attainment of the previous generation in our samples’ district of birth in order to absorb as much unobserved heterogeneity as possible. Ideally, we want to use the education attainment of the parents of each individual in our sample. However, we have no such data. Since the average age of our sample is 31, we define the previous generation as those 55 years old or older. Table 3 contains the summary statistics of the outcomes and the explanatory variables.
With the instrumental variable approach, the first stage of the model is Equation 2 and the second stage is Equation 3.

\[
M_{ijk} = \alpha_0 + \alpha_R R_j + \alpha_X X_{ij} + \phi_k + \nu_{ijk} \quad (2)
\]

\[
Y_{ijk} = \beta_0 + \beta_M \hat{M}_{ij} + \beta_X X_{ij} + \phi_k + \varepsilon_{ijk} \quad (3)
\]

where \( R_j \) is the excluded variable in the 2SLS estimation, \( \phi_k \) is the island of birth fixed effects, and the other variables are the same as in Equation 1.

We show the OLS results of Equation 1, with and without the island of birth fixed effects, in Table 4. The table shows that migration is associated with between 4.2 (Column 1) and 4.6 (Column 2) more years of schooling compared to staying in the rural area. Meanwhile, there is no significant relationship between migration and obesity, although there is a significant and large relationship between migration and lower malnourishment. Those who migrated as a child are about 5 to 8 percentage points less likely to be underweight than rural residents. Finally, individuals who moved to the city as children are between 6.5 to 7.3 centimeters taller than those who remained in rural areas.

The 2SLS results, which show the causal effect of migration, are shown in Table 5. It appears that the instrument performs strongly, having a statistically significant first stage F-statistics and passing the usual tests for exclusion restriction. From the first two columns, the causal effect of migration on education attainment is between 4.4 and 5.2 years of additional schooling in the long-term. In a country where most of the adults only have about nine years of education, this effect is very large. The effect of migration with regards to obesity is similarly large in magnitude, between 4.1 and 10.1 percentage points lower probability of being obese as adults, but is imprecisely estimated. However, we can rule out any large detrimental effect of childhood migration on adult obesity. More importantly, however, is the dramatic effect of migration on malnourishment. Childhood migration lowers the probability to be underweight by around 15 percentage points. Finally, although the effect of migration on height is between -1.4 and 4.2 centimeters, it is not statistically significant.

In summary, our findings show that children who followed their migrant parents to the city enjoy a large benefit with regards to education attainment. In addition, their risk of malnourishment is
significantly reduced compared to staying in the rural districts. However, we find no effect of migration on height, which is a long-term indicator of health. This is probably due to the fact that the youngest child in our sample moved when he or she was five years old. It is possible that we could get a different result if we look at children who moved to the city as an infant. Finally, comparing the OLS and 2SLS results, it appears that the OLS underestimates the effect of migration on education attainment and malnourishment but overestimates the effect on height.

What are the possible mechanisms that may explain our findings of a positive effect of childhood migration on education and health? As we mention in the introduction, these mechanisms may include differences in the availability of health and education facilities between urban and rural areas or the higher returns to education and health investments in urban areas. We discuss these two aspects in turn.

In Indonesia, inequality in the availability of health and education facilities between urban and rural areas is large. In a review paper, Darja et al (2005) find that as late as in 1999, only 30% of rural villages in Indonesia had a junior secondary school, while about 9% had a public senior secondary school. In contrast, 88% of urban villages had a junior secondary school, and 64% had a senior secondary school. Given that the average age of our sample is 33 years, secondary school availability in rural areas must have been even worse in late 1980s, the time our sample was at secondary school age. However, the difference in the availability of health facilities between urban and rural areas is not as large. In the same paper, Darja et al (2005) find that in 1999, about 37% of rural villages had a public health center, compared to 52% of urban villages. Although it is true that there was practically no hospital in rural areas, the public health centers are the main provider of healthcare in Indonesia. Therefore, the relatively smaller gap in the access to these centers may explain the relatively small effect of migrating to urban areas on health outcomes.

The second mechanism that could explain the higher education attainment of childhood migrants compared to those who remained in the rural area pertains to the returns to investment in education. Assuming a perfect access to credit market, a parent would continue to invest in their children’s schooling if the net returns to additional schooling are larger than the net returns to an alternative investment. Based on this concept, it appears that the net returns to investment in education becomes smaller than the returns to an alternative investment at quite an early stage of education in rural areas, but happens much later in urban areas. However, empirically testing this hypothesis would entail measuring the net returns to all alternative investment choices, including a child’s education. We know of no such dataset in Indonesia that would allow us to empirically test this conjecture. Perhaps for this reason, we find almost no empirical research on this issue in the literature.6

Note that merely comparing the returns to education in urban and rural areas separately is not adequate for this purpose. Establishing higher returns to education in urban areas compared to rural areas is not a sufficient explanation, because when the decision whether to invest in additional schooling for the child is taken, a decision maker is comparing the returns of the investment to returns of alternative investments in the area where he or she resides, not in other areas.

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6 Note that merely comparing the returns to education in urban and rural areas separately is not adequate for this purpose. Establishing higher returns to education in urban areas compared to rural areas is not a sufficient explanation, because when the decision whether to invest in additional schooling for the child is taken, a decision maker is comparing the returns of the investment to returns of alternative investments in the area where he or she resides, not in other areas.
VI. Conclusion

Developing countries are experiencing unprecedented levels of urbanization. Although most of these movements are motivated by economic reasons, it is possible that they affect the human capital accumulation of the children who follow their parents to the cities. The issue is an important one, as it addresses an externality that, if turns out to be negative, may require government intervention.

This paper estimates the causal effect of permanently migrating as a child from a rural area to an urban area on human capital outcomes. To our knowledge, this paper is one of only several papers, especially in the context of a developing country, which is able to estimate the causal effect of migration. In the context of Indonesia, we hope that this is the first step in what is an increasingly important area of research as the country continues to urbanize.

We utilize a recent survey of urban-rural migrants in Indonesia, the RUMiCI, and merge it with the National Socioeconomic Survey to create a dataset that contains the migrants in urban areas and non-migrants in rural areas who were born in the same rural districts. We employ a measure of district-level propensity to migrate, calculated from the Indonesian intercensal survey, as an instrument.

To summarize the findings, we find childhood migration to urban areas increased education attainment by about four more years of schooling relative to an observably similar individual who remained in the rural area. In addition, the childhood migrants are significantly healthier, facing a lower probability to be underweight by about fourteen percentage points. However, we find no statistically significant effect on height, which is a measure of long-term health.

There are many channels through which migration could affect an individual’s human capital outcomes. These include increased food intake, improved health practices, higher access to quality education and health facilities, higher labor market returns to education and health, or peer effects. However, we do not have sufficient information to determine which channel is dominant. Therefore, we leave the investigation into potential channels for future studies.

References


Figure 1. Human Capital Outcomes: Migrants and Non-Migrants

Note: Lines are polynomial fit
### Table 1. Population and Rural-Urban Migrants in the RUMiCI Cities, 2005

<table>
<thead>
<tr>
<th>City</th>
<th>Population Total N (Thousands)</th>
<th>Rural-to-Urban Migrants N (Thousands)</th>
<th>Share to City Population (%)</th>
<th>Children N (Thousands)</th>
<th>Share to Migrant Population (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Medan</td>
<td>2,030</td>
<td>275</td>
<td>13.5</td>
<td>46</td>
<td>16.7</td>
</tr>
<tr>
<td>Tangerang</td>
<td>1,452</td>
<td>348</td>
<td>24.0</td>
<td>44</td>
<td>12.6</td>
</tr>
<tr>
<td>Samarinda</td>
<td>574</td>
<td>189</td>
<td>32.9</td>
<td>25</td>
<td>13.2</td>
</tr>
<tr>
<td>Makassar</td>
<td>1,194</td>
<td>332</td>
<td>27.8</td>
<td>48</td>
<td>14.5</td>
</tr>
</tbody>
</table>

### Table 2. Living Arrangement for Children of Migrants

<table>
<thead>
<tr>
<th>City</th>
<th>N</th>
<th>Live with household head in urban areas</th>
<th>Live in rural area</th>
<th>Live elsewhere in the urban areas</th>
<th>N born in rural areas</th>
<th>Live with household head in urban areas</th>
</tr>
</thead>
<tbody>
<tr>
<td>Medan</td>
<td>604</td>
<td>591</td>
<td>3</td>
<td>10</td>
<td>30</td>
<td>30</td>
</tr>
<tr>
<td>Tangerang</td>
<td>459</td>
<td>366</td>
<td>72</td>
<td>21</td>
<td>33</td>
<td>33</td>
</tr>
<tr>
<td>Samarinda</td>
<td>394</td>
<td>368</td>
<td>13</td>
<td>13</td>
<td>54</td>
<td>54</td>
</tr>
<tr>
<td>Makassar</td>
<td>447</td>
<td>408</td>
<td>16</td>
<td>23</td>
<td>119</td>
<td>119</td>
</tr>
<tr>
<td>Total</td>
<td>1,904</td>
<td>1,733</td>
<td>104</td>
<td>67</td>
<td>236</td>
<td>236</td>
</tr>
</tbody>
</table>


<table>
<thead>
<tr>
<th></th>
<th>Non-migrants (Lived in rural areas)</th>
<th>Migrants (Permanently moved to the city as a child)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Outcome variables</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Education attainment (years)</td>
<td>5.938 (4.002)</td>
<td>9.242 (4.576)</td>
</tr>
<tr>
<td>Obese (Yes = 1)</td>
<td>0.020 (0.141)</td>
<td>0.046 (0.211)</td>
</tr>
<tr>
<td>Underweight (Yes = 1)</td>
<td>0.171 (0.376)</td>
<td>0.060 (0.237)</td>
</tr>
<tr>
<td>Height (cm)</td>
<td>148.528 (16.720)</td>
<td>156.668 (13.821)</td>
</tr>
<tr>
<td><strong>Independent variables</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Migrated (Yes = 1)</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Female (Yes = 1)</td>
<td>0.502 (0.500)</td>
<td>0.459 (0.499)</td>
</tr>
<tr>
<td>Age (years)</td>
<td>32.099 (19.263)</td>
<td>34.293 (16.588)</td>
</tr>
<tr>
<td>Married (Yes = 1)</td>
<td>0.530 (0.499)</td>
<td>0.785 (0.411)</td>
</tr>
<tr>
<td>Household size</td>
<td>4.639 (1.828)</td>
<td>4.254 (2.243)</td>
</tr>
<tr>
<td>Distance to nearest primary school (km)</td>
<td>0.394 (2.923)</td>
<td>0.097 (0.740)</td>
</tr>
<tr>
<td>Distance to nearest junior secondary (km)</td>
<td>3.270 (5.484)</td>
<td>4.967 (27.619)</td>
</tr>
<tr>
<td>Distance to nearest public health center (km)</td>
<td>0.963 (0.189)</td>
<td>0.915 (0.279)</td>
</tr>
<tr>
<td>Distance to subdistrict capital (km)</td>
<td>7.322 (8.988)</td>
<td>7.227 (9.248)</td>
</tr>
<tr>
<td>Average education attainment of previous generation in district (years)</td>
<td>3.657 (1.041)</td>
<td>3.978 (1.287)</td>
</tr>
</tbody>
</table>

Note: standard deviations are in parentheses.
Table 4. The Correlation between Childhood Migration and Human Capital Accumulation, Least Squares Estimation

<table>
<thead>
<tr>
<th></th>
<th>Education attainment (years)</th>
<th>Obese (Yes = 1)</th>
<th>Underweight (Yes = 1)</th>
<th>Height (cm)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS</td>
<td>OLS</td>
<td>LPM</td>
<td>LPM</td>
</tr>
<tr>
<td>Migrated (Yes = 1)</td>
<td>4.179***</td>
<td>4.660***</td>
<td>0.035</td>
<td>0.030</td>
</tr>
<tr>
<td></td>
<td>(0.374)</td>
<td>(0.391)</td>
<td>(0.031)</td>
<td>(0.030)</td>
</tr>
<tr>
<td>Female (Yes = 1)</td>
<td>-0.740***</td>
<td>-0.761**</td>
<td>0.045</td>
<td>0.040</td>
</tr>
<tr>
<td></td>
<td>(0.271)</td>
<td>(0.302)</td>
<td>(0.027)</td>
<td>(0.025)</td>
</tr>
<tr>
<td>Age (years)</td>
<td>-0.035***</td>
<td>-0.036***</td>
<td>0.001</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Married (Yes = 1)</td>
<td>1.710***</td>
<td>1.724***</td>
<td>-0.053</td>
<td>-0.044</td>
</tr>
<tr>
<td></td>
<td>(0.188)</td>
<td>(0.242)</td>
<td>(0.052)</td>
<td>(0.047)</td>
</tr>
<tr>
<td>Household size</td>
<td>-0.153*</td>
<td>-0.140</td>
<td>-0.004</td>
<td>-0.003</td>
</tr>
<tr>
<td></td>
<td>(0.082)</td>
<td>(0.088)</td>
<td>(0.005)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Distance to nearest primary school (km)</td>
<td>-0.015</td>
<td>-0.013</td>
<td>0.001</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
<td>(0.021)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Distance to nearest junior secondary (km)</td>
<td>-0.009***</td>
<td>-0.008***</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Distance to nearest public health center (km)</td>
<td>0.482</td>
<td>0.402</td>
<td>0.025</td>
<td>0.032</td>
</tr>
<tr>
<td></td>
<td>(0.728)</td>
<td>(0.704)</td>
<td>(0.017)</td>
<td>(0.022)</td>
</tr>
<tr>
<td>Distance to subdistrict capital (km)</td>
<td>-0.012</td>
<td>-0.005</td>
<td>-0.002</td>
<td>-0.002</td>
</tr>
<tr>
<td></td>
<td>(0.029)</td>
<td>(0.028)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Average education attainment of previous generation in district (years)</td>
<td>0.395***</td>
<td>0.463***</td>
<td>0.016</td>
<td>0.019</td>
</tr>
<tr>
<td></td>
<td>(0.114)</td>
<td>(0.133)</td>
<td>(0.010)</td>
<td>(0.013)</td>
</tr>
<tr>
<td>Constant</td>
<td>5.708***</td>
<td>5.187***</td>
<td>-0.071*</td>
<td>-0.097</td>
</tr>
<tr>
<td></td>
<td>(1.173)</td>
<td>(1.114)</td>
<td>(0.043)</td>
<td>(0.064)</td>
</tr>
<tr>
<td>Island of birth fixed effects</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>N</td>
<td>102,277</td>
<td>102,277</td>
<td>81,183</td>
<td>81,183</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.431</td>
<td>0.417</td>
<td>0.069</td>
<td>0.062</td>
</tr>
</tbody>
</table>

Notes: *** 1% significance, ** 5% significance, * 10% significance; standard errors in parentheses are robust to heteroskedasticity and clustered at district of birth; OLS is Ordinary Least Squares, LPM is Linear Probability Model.
Table 5. The Effect of Childhood Migration on Human Capital Accumulation, 2SLS Estimation

<table>
<thead>
<tr>
<th>Education attainment (years)</th>
<th>Obese (Yes = 1)</th>
<th>Underweight (Yes = 1)</th>
<th>Height (cm)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
</tr>
<tr>
<td>Migrated (Yes = 1)</td>
<td>4.361***</td>
<td>5.172***</td>
<td>-0.101*</td>
</tr>
<tr>
<td></td>
<td>(0.848)</td>
<td>(0.607)</td>
<td>(0.062)</td>
</tr>
<tr>
<td>Female (Yes = 1)</td>
<td>0.721***</td>
<td>-0.683**</td>
<td>0.023</td>
</tr>
<tr>
<td></td>
<td>(0.266)</td>
<td>(0.286)</td>
<td>(0.025)</td>
</tr>
<tr>
<td>Age (years)</td>
<td>-0.035***</td>
<td>-0.034***</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Married (Yes = 1)</td>
<td>1.655***</td>
<td>1.530***</td>
<td>-0.018</td>
</tr>
<tr>
<td></td>
<td>(0.298)</td>
<td>(0.297)</td>
<td>(0.047)</td>
</tr>
<tr>
<td>Household size</td>
<td>-0.150*</td>
<td>-0.131</td>
<td>-0.008</td>
</tr>
<tr>
<td></td>
<td>(0.089)</td>
<td>(0.092)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>Distance to nearest primary school (km)</td>
<td>-0.012</td>
<td>-0.002</td>
<td>-0.002</td>
</tr>
<tr>
<td></td>
<td>(0.030)</td>
<td>(0.027)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Distance to nearest junior secondary (km)</td>
<td>-0.009***</td>
<td>-0.009***</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Distance to nearest public health center (km)</td>
<td>0.505</td>
<td>0.516</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>(0.745)</td>
<td>(0.716)</td>
<td>(0.015)</td>
</tr>
<tr>
<td>Distance to subdistrict capital (km)</td>
<td>-0.011</td>
<td>-0.004</td>
<td>-0.002</td>
</tr>
<tr>
<td></td>
<td>(0.029)</td>
<td>(0.027)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Average education attainment of previous generation in district (years)</td>
<td>0.390***</td>
<td>0.408***</td>
<td>0.022*</td>
</tr>
<tr>
<td></td>
<td>(0.123)</td>
<td>(0.154)</td>
<td>(0.013)</td>
</tr>
<tr>
<td>Constant</td>
<td>5.979***</td>
<td>5.047***</td>
<td>0.033</td>
</tr>
<tr>
<td></td>
<td>(1.376)</td>
<td>(1.133)</td>
<td>(0.043)</td>
</tr>
<tr>
<td>Island of birth fixed effects</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>N</td>
<td>102,277</td>
<td>102,277</td>
<td>81,183</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.430</td>
<td>0.415</td>
<td>0.019</td>
</tr>
<tr>
<td>First stage F-stat</td>
<td>10.125</td>
<td>31.012</td>
<td>11.996</td>
</tr>
</tbody>
</table>

Notes: *** 1% significance, ** 5% significance, * 10% significance; standard errors in parentheses are robust to heteroskedasticity and clustered at district of birth; instrument used in 2SLS estimations are the number of migrants from a rural district who are living in each of the four cities divided by the number of population in the rural district.