# Parental Rural-Urban Migration and Child Education

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**Abstract**

Parental migration and family separation are key factors affecting the outcomes of the next generation. This paper examines the joint household decision of parental rural-urban migration and children's education in China, where the *Hukou* system restricts migrants' access to urban public services. I develop a nested discrete choice model that incorporates expected returns to children's education as part of the parental migration decision. Estimation results using household panel data show that rural parents migrate for better educational opportunities for their children and a wage premium, avoiding high costs but still concentrating in the most restrictive and congested destinations. Counterfactual analyses suggest that education subsidies at the rural origin of migrants are more effective than subsidies at the destination, or even a universal subsidy, in reducing family separation and improving children's school performance. And all education subsidies are more effective than mobility restrictions in controlling migration flows without harming the usually hidden but highly vulnerable group in labor migration - children, suggesting that policies targeting the motivation for migration are more effective than mobility frictions in controlling migration.

*Keywords*: Internal Migration, Migration Frictions, *Hukou*, Child Education, Family Separation

*JEL codes*: D13, J13, I25, J61, R12, R23

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# 1 Introduction

Both investments in time and resources for human capital are key to child development, while parents with migration opportunities may compromise parental attention for improved household economic circumstances. Parental migration eases liquidity constraints on households (Edwards and Ureta, 2003; Du et al., 2005) and promotes increased investment in children (McKenzie and Rapoport, 2011; Ambler et al., 2015), but it is often associated with parental absence from the home and may negatively affect children's educational attainment due to a lack of parental care (Lahaie et al., 2009) or an increase in the amount of time left-behind children spend working on farms or in households (Chang et al., 2011); Antman, 2011), although child labor is expected to decrease as household budget constraints ease. And for younger children, who require more direct care and supervision, these negative effects may be particularly pronounced.

This paper argues that parents do migrate for better educational opportunities for children, and policies targeting this motivation can effectively affect child outcomes. In order to fully explore the channel through which parental migration affects children's education, this paper attempts to answer the following questions: how are parents' work locations and children's school locations jointly decided by the household, and how is the substitution between different destinations affected by the benefits and costs of children's education, and how are children's educational outcomes affected, and what policies would be most effective in improving the welfare of rural-urban migrants and their children.

This paper develops and estimates a nested model of parental migration decisions and children's educational decisions to address the questions raised above. Parents are active decision makers who choose their work location and their children's school location in a nested setting. Migrants are defined as the "floating population" who live and work in urban areas without local citizenship and are therefore limited in many social services at destination, including health care, housing, and education. City governments impose strict requirements on the migrant's access to local citizenship, which discourages migrants from bringing their children to the destination, as urban public schools generally accept only local children.

The main hypothesis to be tested is the following: migrant parents do invest more in their children compared to the non-migrant counterparts, whatever the children are separated from them or not. A lower probability of settlement will lead migrants to place more weight on the urban wage premium and less weight on the high urban price. Since there is a very high probability that their extended families will be left behind, and if so, they will compromise their consumption at the destination while partially consuming elsewhere (where their families live). Since lower prices in rural areas are also associated with lower quality of education[1]. For parents who are concerned about their children's outcomes, they worry that the children left behind will have lower educational outcomes. If migrants who go to restrictive urban areas[2] to chase the high urban wage premium without being able to bring the children with them, they will use the extra resources gained from migration to improve the quality of their children's education, for example, by sending the child to a place with better educational quality than the schools in their rural origin, such as nearby towns.

The main challenges in testing this hypothesis include the endogeneity of the migration decision and the issue of the selectivity of household migration. Migration decisions are endogenous to the socio-economic background of households, and both migration and mobility restrictions are endogenous to the characteristics of the destination. And when it comes to household migration, there is also the selection into whether the whole household migrates, the selection into return migration, and when to return (Antman, 2013). To address this concern, a nested model is developed with several instruments that measure the institutional costs of migration.

The reduced-form evidence shows that the quality of schools differs across different types of locations. The structural model then examines how parents migrate, taking into account the costs and benefits of migration as well as the expected gains from children's education, and how they send their children to schools in different locations conditional on the migration decision. The nested setting includes both the binary choice to migrate and the binary choice to leave children behind. If the place of work does not match the place of origin of the household, the head of the household can be considered a migrant, and if the place of school does not match the place of work of the parents, we can conclude that the child is left behind. Compared to the model that includes only binary decisions, this model is more comprehensive and includes more layers of location choices and educational inputs for the child: migration to different types of locations is decided by the household, and migration and educational gains are also calculated for specific location choices.

In the model, households exogenously born in rural areas are assumed to have a choice of working in different types of locations and a choice of having their children study in different locations relative to the working location. To estimate the model, expected

[1] Children left behind are usually cared for by relatives with lower levels of education, most likely grandparents, according to Zhong (2024).

[2] the more restrictive regions tend to be more attractive at the same time (Zhang et al., 2020).

wages and housing prices are predicted for different job locations, while wages are also predicted for different ages and education levels of the worker with a nonlinear setting. This variation facilitates the estimation of substitution across job locations. Similarly, the expected outcomes and costs of children's education are predicted for households choosing different school locations with children of different gender and age. This allows the estimation of substitution across school locations.

The value of migration can be reflected in the stringency of the destination. For mobility frictions, several measures of the stringency of institutional barriers are adopted, including a current index, a sample propensity, and a historical predictor of *Hukou* stringency. A current index (Zhang et al., 2019) captures the variation in *Hukou* stringency from 2000 to 2016, while a concern is that migration flows are endogenous to this measure, then a historical measure of the city's population capacity until 2000 is used as an alternative instrument. The value of migration comes from the attractiveness of the destination, and more attractive destinations tend to be more restrictive, as restrictions are set based on the population capacity of the city and the migration inflow to the city. One concern with using the above two indices is that they only have variation for the large cities, and therefore can't distinguish between migrants' preference for the small cities. The sample conversion rate of citizenship is then used to capture the variation of migrants' willingness to convert their *Hukou* status to local, and this helps to estimate the preference parameters on the sample of destinations that are less restrictive and has little variation in the previous two measures.

The main parameters of the model are then estimated using a sequential estimation procedure that first estimates the lower nest of the school location decision and then incorporates the gains from child education in the upper nest of the work location decision. In the upper nest, parents first choose between different types of locations: rural, urban, or urban, and then an exact location is realized in the pool of each type. Relative to the parents' work location, the household then decides the child's school location. The model framework is then used to explore various counterfactuals, including rural and urban education subsidies and a housing price decline, which capture the recent reality in China.

The model parameter estimates confirm selection into migration by socioeconomic conditions and sorting into different destinations. They show that parents migrate for better educational opportunities for their children and the wage premium, avoiding high costs, but still concentrated in the most restrictive and congested destinations. Counterfactual analyses suggest that subsidizing education at the rural origin of migrants is more effective than subsidizing education at the destination, or even universal subsidy, in reducing family separation and improving children's schooling. And in terms of controlling migration flows, all education subsidies are more effective than mobility restrictions. Instead of restricting mobility and leaving households to bear all the costs of the lack of local services and the break-up of families, a more effective approach would be to identify and target the reasons for migration.

My model and empirical results provide a novel framework for considering child outcomes in family migration under mobility frictions. Migration frictions decide whether they migrate, where they migrate, and how they migrate: how migrant parents manage their children. My model is used to evaluate the effects of the migration policy in the Chinese context, and can also be applied to understand the long-run role of internal migration barriers which are common especially in developing countries.

**Related Literature** My paper belongs primarily to the literature on parental decisions and child outcomes (reviewed by Francesconi and Heckman, 2016). Previous work has mainly focused on the impacting channel of the balance between parental earning capacity and financial transfers (Antman, 2012, Ambler et al., 2015, Bai et al., 2018, Albert and Monras, 2022) and parental time and attention (Constant and Zimmermann, 2013, Marchetta and Sim, 2021, Yang and Bansak, 2020). Recent literature also includes the role of other extended families in child development (Gao et al., 2023, Zhong, 2024). My paper contributes to this literature by further considering children's school location and treating it as an important input in the child development process, as the quality of schools varies significantly across different types of locations.

My work is related to the literature on structural models of migration that examine the role of migration policies (e.g., Bryan and Morten, 2019, Tombe and Zhu, 2019, Lagakos et al., 2023, Adamopoulos et al., 2024). The existing literature has mainly focused on individual decisions rather than family considerations, and the effects of migration on household welfare are less well understood. Recent literature has discussed household migration decisions and related welfare effects (Gao et al., 2023, Imbert et al., 2024, Zhong, 2024). I contribute to this literature by developing a model that allows for the joint determination of parental migration decisions and children's educational inputs, which are made relative to the parents' migration decision. This reveals the effects of migration policies on children's educational outcomes and other intra-household channels of migration that are previously unobservable in less complex settings.

My work also contributes to the literature on urbanization in developing contexts (e.g., Selod and Shilpi, 2021, Garriga et al., 2023). Given the rapid process of urbanization in economies like China, the definition of rural-urban migrants is complicated and dynamic, about 43.7% of people of rural origin moving across counties by 2022 (according to my data, explained later in the Data section) will come from rural areas that urbanize after their birth, which means that these individuals will be defined as migrants in some analyses (based on the previous rural-urban classification of their *Hukou* register or based on a simple comparison of their rural-urban classification over time) and as non-migrants in another analysis (based on the current rural-urban classification of their *Hukou* register), while both definitions may be valid in different contexts but have different implications for household welfare. My paper contributes to this literature by introducing a tripartite classification of location: "rural", "town", and "city". The "town" destinations are less restrictive than the "city" locations, and this allows for a more comprehensive understanding of the effects of migration policies on household welfare.

**Paper Overview** The paper is organized as follows. Section 2 presents the institutional background. Section 3 introduces the dataset I use and describes the economic and behavioral characteristics of rural households with migration opportunities. Section 4 presents a household model with nested migration and school location choices. Section 5 discusses the estimation procedure and the model estimates. Section 6 uses the model estimates to assess the role of mobility frictions and simulates different policies targeting parents or children, at the origin or at the destination, and discusses the policy effects on each group and on migration decisions. Section 7 concludes the paper.

# 2 Institutional Background

Recent economic growth in developing countries such as China has largely been driven by the huge influx of cheap rural labor leaving their villages to work in the manufacturing sector in urban areas. Although the overall productivity effects of rural-urban migration have been shown to be positive (Bryan and Morten, 2019, Lagakos et al., 2023), the urban congestion (Akbar et al., 2023) and environmental effects (Chen et al., 2022) continue to concern policymakers. Governments in less developed countries and regions were much more likely (78 percent) than those in more developed countries (51 percent) to have adopted policies to reduce rural-urban migration (United Nations, 2015), reflecting the more acute challenges faced by the least developed countries in their urbanization process.

China's rural-urban household division has its roots in the introduction of the household registration system, commonly known as the *Hukou* system. The *Hukou* system links access to certain local social services to the place of household registration, usually the place of birth.[3] Residents receive their *Hukou* booklets at birth. A new member born or married into a household is added to the *Hukou* booklet and has the same rural-urban classification as other members. Large cities, especially megacities,[4] set requirements for migrant applicants to meet before they can obtain a local *Hukou*. Typically, requirements are set for social insurance participation, education level, investment and real estate purchase, and employment conditions, etc.

In the Chinese context, the majority of rural-urban migrants are low-skilled workers who often do not meet the criteria for urban *Hukou* status in large cities. According to my data (CFPS, waves 2010-2022), only 58.3% of the rural parents (the parents of all rural *Hukou* holders) have completed middle school[5]. As a result, without local *Hukou*, migrants are unable to access basic local social services such as health care and education for themselves and their families. This has created significant challenges for the resettlement of migrant families.

The introduction of China's *Hukou* system dates back to 1958, the beginning of the 3-year famine, and was designed to curb rural-urban migration and ensure adequate food production. There are four phases of development of the *Hukou* system since it's introduction (Song, 2014, Meng et al., 2015, Kinnan et al., 2018, Zhang et al., 2020, Adamopoulos et al., 2024). Between 1958 and the late 1970s, labor migration was illegal in China unless arranged by the government. From the early 1980s to 2000, restrictions on rural *Hukou* holders moving to cities to work were relaxed, while basic services such as food provision were still tied to a household's place of registration, severely limiting the ability of individuals to work outside their place of origin for extended periods of time. After 2000, food provision and place of registration were separated, but the type of *Hukou* continued to determine access to public goods. In 2014, the distinction between agricultural and

[3]Before 2014, the *Hukou* distinguished between agricultural and non-agricultural households, commonly known as rural and urban households. Although the rural-urban classification has not been printed on newly issued *Hukou* booklets since the 2014 reform, all respondents in my data (constructed from the *China Family Panel Studies* (CFPS, explained in section 3)) still know their *Hukou* type.

[4]According to the 2010 Chinese census, there are 7 cities in mainland China that have more than 10 million people living in each of their urban areas.

[5]Compulsory education in China: 6 years of primary school and 3 years of middle school.

non-agricultural *Hukou* in the same place was eliminated, making all residents eligible for the same local public services. While research (Zhang et al., 2019) argues that the 2014 reform is limited to small cities and actually makes megacities even more restrictive to migrants, especially in restricting migrant children's access to local schools (Chan, 2018). Wu and You (2024) confirms that the proportion of migrants obtaining local *Hukou* also experienced a pronounced decline between 2000 and 2020.

Cai et al. (2001) found that there was a significant positive correlation between the planned migrant population in each city in 1952-1998 and the annual per capita food production in the previous year. This is due to the fact that before 2000, when food supply was still tied to a household's place of registration and there were high costs of commodity circulation, a city's grain production determined its population capacity and was used by the government to determine the stringency of *hukou* registration. Zhang et al. (2020) then suggests using the level of grain reserve before 2000 as an instrument for migration.

While the process of urbanization has brought many benefits to people from rural areas, such as improved living standards and employment opportunities, restrictions on mobility have negative consequences that offset these benefits: Not only do undocumented migrants lack access to many formal long-term jobs, which can result in a significant wage penalty (Borjas and Cassidy, 2019) and worse living conditions at destination, as migrant workers disproportionately move to expensive and restrictive cities (Imbert et al., 2024), but the costs of mobility restrictions are mainly borne by their children and other extended families. Nearly half (49.2%) of rural-urban migrants without urban citizenship in China choose to leave their children behind in rural areas as of 2005 (Gao et al., 2023). And the children left behind are much more likely to be cared for by grandparents (71%) than their counterparts living with their parents (20%) (Zhong, 2024).

For the children left behind by their migrant parents in the sending regions, while there is the possibility that remittances can alleviate families' liquidity constraints and thus improve children's educational outcomes, the absence of parental care and guidance can have long-lasting effects on children's emotional and cognitive performance that may outweigh the positive effects of remittances. According to recent estimates (Tang and Wang, 2021), there are approximately 61 million left-behind children in rural China, accounting for 37.7 percent of all rural children and 21.88 percent of all children nationwide. Figure 1 (generated using my data, explained later in the Data section) shows that the left-behind children are less likely to attend school and also have lower educational outcomes than their counterparts who live with their parents.

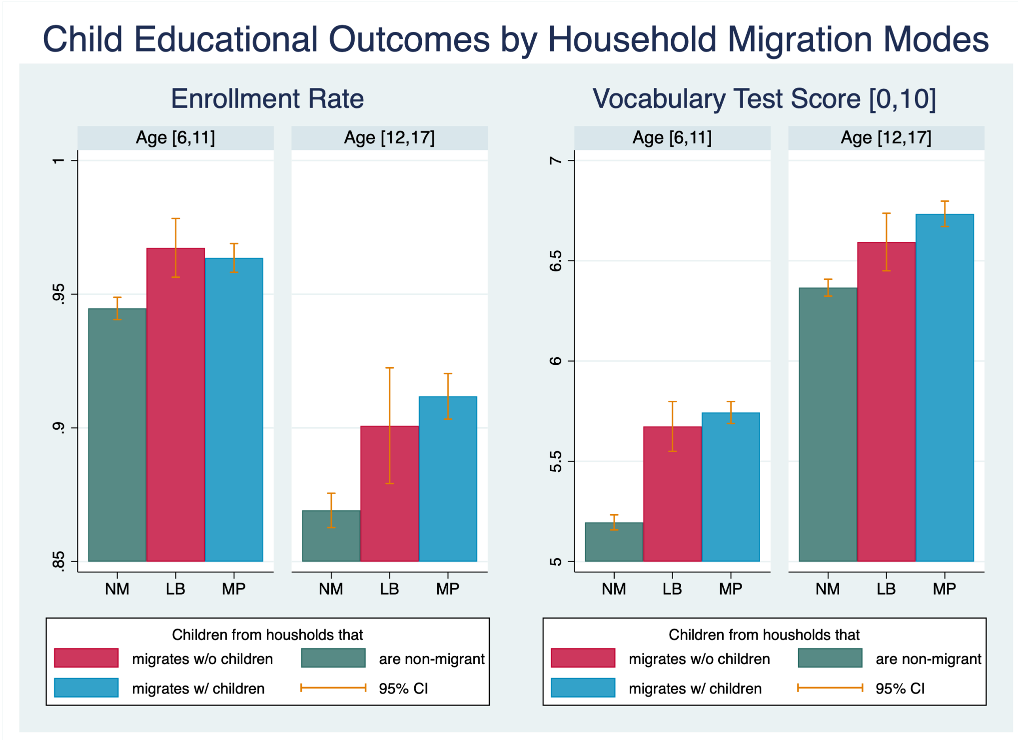



Figure 1: Comparison of Child Educational Outcomes by Group
*Data Source*: CFPS 2010-2020.

# 3 Data

In this section, I present how I collect and construct my data and describe the economic and behavioral characteristics of rural households with migration opportunities that motivate the model and the empirical analysis.

## 3.1 Data and Terms

My data are collected from the China Family Panel Studies (CFPS) project.[6] I restrict my sample to children with rural *Hukou* and their households.[7] After I get the sample of all these households, if there is more than one child sampled from the same household, the youngest child is kept to avoid possible correlation.

The term "migrant" is then defined as someone who is registered with a rural *Hukou* but attends school or works in an urban place, and in addition, this separation of place of registration and place of residence is because one has moved across counties.[8] Most of the literature in this context only defines the migrant based on the separation of *Hukou* place of registration and place of residence, I add the cross-county movement variable to the definition.[9], so that the rural-urban migrants within commuting distance are excluded from the sample, and more importantly, this rules out the possibility that a non-migrant is defined as a migrant just because his or her place of residence changes from rural to urban (according to the National Bureau of Statistics of China's definition) in the rapid urbanization process. According to my data (CFPS 2010-2022), about 20.85% of rural-born urban residents aged 18-65 came from places that have urbanized (classified as rural when they were born, but classified as urban during the survey period).

For the rural-urban division, I adopt the division of urban areas into two types: "town" and "city". Type "town" refers to rural county sear, township and suburb, and type "city" are more developed areas. Both divisions (rural/urban and rural/town/city) are reported by the CFPS survey, based on the classification of the National Bureau of Statistics of China.

[6]The CFPS project (Peking University, 2015) is a national household survey with 7 waves now available: 2010, 2012, 2014, 2016, 2018, 2020, 2022. The baseline target sample of the CFPS consists of 16,000 households in 25 out of a total of 31 provincial-level administrative divisions in mainland China, representing 95% of China's population. Follow-up surveys will be conducted on all these individuals and on the new members as they form new households. Table A1 shows the sample sizes of the CFPS data across waves by the age of the individuals sampled.

[7]I define rural households based on the children's rural-urban classification. The main reason is that it is possible in the data that the migrant parents have changed their *Hukou* registration to the destination, but the child still has the *Hukou*, and in this case the child doesn't have access to public services in the destination based on his or her own citizenship. Although in my data it's more likely that the parents will convert the child's *Hukou* before doing so for themselves, with the most likely reason being that they want to improve the child's educational opportunities.

[8]For each individual, location data are available at his or her birth and over the survey horizon: 2010-2022.

[9]In China, a county can be identified by the 6-digit postal code, where digits 1-2 identify the province and digits 3-4 identify the prefecture.

Table 1: Descriptive statistics of enrolled children aged [6,18]

| Parent Work Location | Child School Location | Count (Share) | Age | Word Score, Z-Score | Math Score, Z-Score | Edu. Expenses |
|---|---|---|---|---|---|---|
| Rural | Rural | **1,494** (75.53%) | 11.22 (0.03) | 0 (0.01) | -0.05 (0.01) | 0.84 (0.02) |
| Rural | Town (O) | 325 (16.44%) | 13.5 (0.07) | **0.06** (0.03) | **0.24** (0.03) | 2.42 (0.1) |
| Rural | City (O) | 159 (8.03%) | **14.25** (0.11) | -0.04 (0.04) | 0.16 (0.03) | **3.93** (0.22) |
| Town | Rural | **296** (43.70%) | 10.54 (0.07) | 0.14 (0.04) | 0 (0.04) | 1.21 (0.09) |
| Town | Town (O) | 170 (25.05%) | 11.93 (0.11) | 0.21 (0.04) | 0.18 (0.03) | 1.6 (0.11) |
| Town | City (O) | 35 (5.20%) | **12.88** (0.22) | **0.44** (0.08) | 0.33 (0.07) | 2.95 (0.49) |
| Town | Town (W) | 109 (16.14%) | 11.51 (0.14) | 0.24 (0.07) | 0.23 (0.06) | 1.81 (0.15) |
| Town | City (W) | 67 (9.90%) | 12.35 (0.18) | 0.42 (0.07) | **0.35** (0.07) | **4.16** (0.34) |
| City | Rural | **133** (38.35%) | 11.56 (0.12) | **0.35** (0.05) | 0.14 (0.05) | 3.06 (0.29) |
| City | Town (O) | 28 (8.15%) | 11.78 (0.23) | 0.27 (0.11) | 0.31 (0.12) | 2.16 (0.36) |
| City | City (O) | 65 (18.81%) | **12.31** (0.17) | 0.28 (0.06) | 0.29 (0.06) | 3.03 (0.38) |
| City | Town (W) | 31 (8.81%) | 11.21 (0.24) | -0.09 (0.23) | **0.52** (0.12) | 2.42 (0.34) |
| City | City (W) | 90 (25.88%) | 11.12 (0.15) | 0.34 (0.07) | 0.2 (0.07) | **3.96** (0.34) |

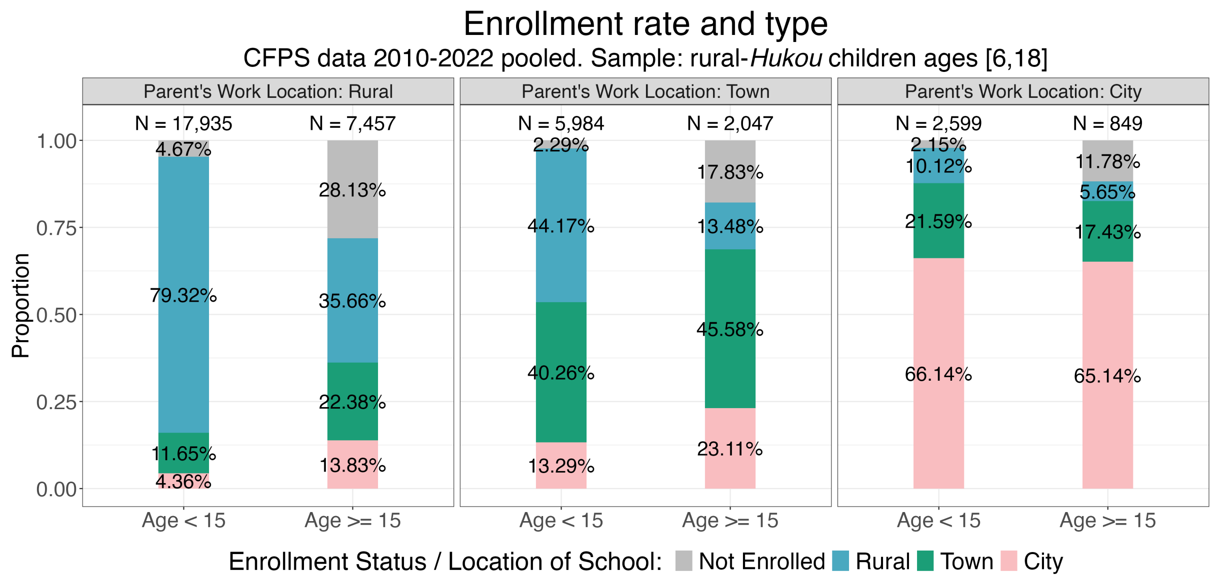
[a] Counts are per-wave counts, averaged over waves 2010 through 2022.
[b] For variables other than counts, standard errors in parentheses.
[c] (O) denotes town/city closest to *Hukou* location. (W) denotes town/city closest to work location.
[d] The money unit is 1,000 CNY deflated to 2010 (around 115 EUR or 147 USD).
[e] Test scores are z-scores adjusted for age and gender.
[f] Bold numbers mark the group maximums by parent work location, while gray numbers mark the group minimums.

## 3.2 Descriptive Statistics

### 3.2.1 Children in Migrant Households

Table 1 shows the descriptive statistics of enrolled children of rural origin by parent's place of work and child's place of school. When classifying the child's school location, if a destination is both closest to the household's origin and closest to the parent's work location, it is counted as closest to the origin. More than 30% of rural parents leave their hometown to work in urban areas, including cities and towns, and the majority of migrant parents go to cities. Among children whose parents work in rural areas or towns, the majority of children are enrolled in rural schools, while among children whose parents migrate to city locations, the majority are enrolled in city schools. This motivates a description of the demographics of the parents to further explore the migration pattern.

Figure 2 shows the percentages by type of location and age group in a histogram and includes the unenrolled children. For non-migrant rural households, children have about an 80% chance of staying in the rural area for school. For children of parents




***Note***: ***1***. Rural or urban refer to the child's *Hukou* type at birth or, if missing, at baseline (2010). ***2***. Compulsory education in China: 6 years of primary school and 3 years of junior secondary school, usually beginning at age 6 and ending at age 15. ***3***. The completion rate of nine-year compulsory education in China was 94% as of 2014 (National Bureau of Statistics of China, 2015).

Figure 2: Child Enrollment by Parent's Work Location

who work in town locations, the chances of children being enrolled in town and rural locations are half to half, with more than 40% of children left behind by migrant parents. For children of parents who work in cities, the majority of children are brought to the destination by their parents, while there is still a significant proportion of about 20% to 30% left behind. Table 1 and Figure 2 together illustrate that these left-behind children are most likely to drop out after the age of 15, when the compulsory 9-year education is about to end. More importantly, about 20% of the children are not enrolled in either the destination or the origin. This suggests that for migrants who have moved to city locations, although the settlement restrictions in big cities limit their ability to bring children to the destination, they still want to use the extra resources they have gained from migration in the educational opportunities of their children, and they are willing to send the children to a place with better educational quality than the schools in their rural origin, such as nearby towns.

For children of parents working in rural areas, under 15 years of age, most of the children are still in compulsory education (9 years, 6 years of primary school plus 3 years of middle school), less than 5% of them are observed not to be enrolled in school. This out-of-school rate rises to about 28% for children between 15 and 18 years of age, when they can legally drop out of school. The non-enrollment rate is lower when the parents work in towns and lowest when the parents work in cities, while in these two cases the expected attention from parents would be lower for rural children compared to all their rural counterparts from non-migrant families. These positive effects of parental migration on children's school enrollment could be due to the fact that this sample has received better education and was in a better economic condition in previous years. These children are selected into families whose parents have a higher chance of working outside the rural areas and are selected to stay in an environment with better educational opportunities.

Besides the fact that above 15 is beyond the compulsory school age and dropping out is allowed, the increase in the proportion of children enrolled outside rural areas across age groups in all three panels of Figure 2 may also be due to differences in school availability for primary and secondary schools. According to my data (CFPS 2010-2022), 7 out of a total of 166 counties[10] have no primary schools, while 77 of them have no secondary schools, and in all counties there are fewer secondary school seats than primary school seats. This suggests that children in these counties have to go to other places for secondary education after they graduate from primary school.

Table 1 also presents the descriptive statistics of the children's test scores and educational expenditures. The math and vocabulary tests are standardized tests administered in the CFPS surveys, so children who are not enrolled in school also take the test, and the scores are comparable every two waves. The scores shown are z-scores adjusted for the child's gender and age, and indicate how the child is doing academically compared to a reference of the same age and gender. Comparing children enrolled in rural and town schools with different parental work locations, we see that children whose parents work in towns perform better on the test, even though they are actually separated from their city migrant parents. From the education expenditures[11], we see that the most expensive locations in terms of educational expenditures are the cities closest to the parents' place of work (note that for city migrants, the city closest to the parents' place of work is the destination itself), and this means that for this pattern to be possible, there must be a significant proportion of migrant parents who choose as their migration destination a more expensive city other than the city closest to their hometown. And we also see that higher test scores are not always associated with higher education spending; there are many other factors that affect a child's academic performance.

[10]County: the third level of administrative division in China. A 6-digit postal code identifies a county, digits 1-2 identify a province, and digits 1-4 identify a prefecture.

[11]Education expenditures include everything they have paid that is related to the child's education: tuition and miscellaneous fees, textbooks, school lunches, boarding fees, school bus fares, visits and exchanges organized by the school, as well as costumes, musical instruments and sports equipment, etc.

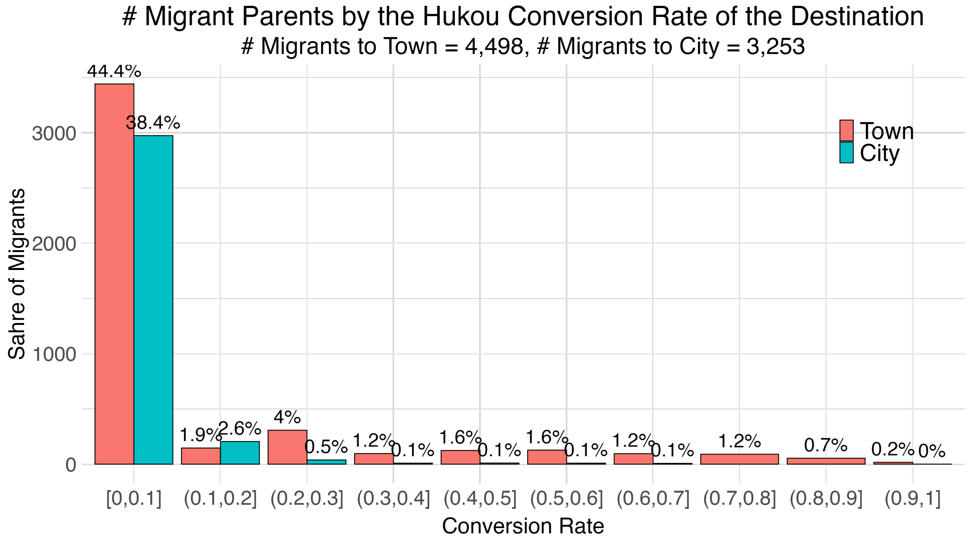



Figure 3: The Concentration of Migrants in Big and Restrictive Cities

*Data Source*: CFPS 2010-2020.

### 3.2.2 Migrant Parents

Figure 3 shows the distribution of the sample of migrant parents across town and city locations by the *Hukou* conversion rate of the destination. The conversion rate is calculated as the number of migrant parents who have converted their *Hukou* registration to the destination divided by the total number of migrant parents in that location. From the figure we can see that migrants are highly concentrated in the most restrictive cities.

Among the sample of all adults aged 19-50 who moved across counties, 29.6% of them migrated to city destinations, 30.3% of them went to town destinations, and the remainder moved across rural counties. For the sample of migrant parents of children aged 6 to 18, about the same proportion (30.9%) of them migrated to towns, but a smaller proportion (20.1%) of them migrated to cities. This suggests that migrant parents are less likely to move far from their rural origin (it is reasonable to assume that there are more towns than cities around an average rural village) and, conditional on migration, are more likely to choose the less restrictive town destinations than the city destinations. For the sample of parents, 58% of them have completed 9-year compulsory education, which is higher than the completion rate of all adults (47.5%). This is consistent with positive selection into migration based on education. These numbers are plotted in Figure A1.

Table 2 shows the characteristics of parents by location of work and location of child's school. The table confirms the positive selection for migration in parents' education level, income, and occupation. For non-migrant households, parents who work in rural areas and send their children to city schools have the best socio-economic background. For town-migrant parents, those who send their children to the city closest to their town of work have the highest value on nearly all demographic indicators. And we also see that town-migrant parents who leave their children behind are not the group with the lowest educational level and income, which is also true for city-migrant parents. The city-migrant parents who bring their children to the destination have the best economic background among all city migrants, which is due to the additional resources they have and the fact that their destination coincides with the first choice on the list of school locations from which they can choose.

Table 2: Descriptive statistics of parents and counts of children by group, pooled data

| | | | | Father | | | | Mother | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Work Location | School Location | Count | No. Children | Age | Completes 9-yr. Edu. | Avg Income | White-collar | Age | Completes 9-yr. Edu. | Avg Income | White-collar |
| Rural | Rural | **10,457** | **1.7** (0.01) | 38.2 (0.1) | 55.5% (0.5%) | 16.4 (0.3) | 8.6% (0.3%) | 36.2 (0.1) | 44.6% (0.5%) | 9 (0.2) | 8.3% (0.3%) |
| Rural | Town (O) | 2,276 | 1.68 (0.01) | 40.3 (0.1) | 59.5% (1.0%) | 20.8 (0.7) | 9.5% (0.6%) | 38.6 (0.1) | 51.0% (1.0%) | 10.8 (0.3) | 10.0% (0.6%) |
| Rural | City (O) | 1,111 | 1.55 (0.02) | **41.3** (0.2) | **65.3%** (1.4%) | **24.5** (0.9) | **13.9%** (1.0%) | **39.6** (0.2) | **51.5%** (1.5%) | **13.8** (0.5) | **12.1%** (1.0%) |
| Town | Rural | **2,074** | **1.64** (0.01) | 37.1 (0.1) | 71.5% (1.0%) | 32.6 (0.9) | 14.9% (0.8%) | 34.9 (0.1) | 63.0% (1.1%) | 20.1 (0.9) | 13.0% (0.7%) |
| Town | Town (O) | 1,189 | 1.58 (0.02) | 39 (0.2) | 63.8% (1.4%) | 20.7 (0.8) | 13.0% (1.0%) | 36.9 (0.2) | 60.2% (1.4%) | 13.5 (0.6) | 13.2% (1.0%) |
| Town | City (O) | 247 | 1.32 (0.03) | **40.5** (0.4) | 76.1% (2.7%) | 37.6 (2.6) | 13.4% (2.2%) | **38.5** (0.4) | **76.5%** (2.7%) | 26.2 (2.1) | 14.2% (2.2%) |
| Town | Town (W) | 766 | **1.64** (0.02) | 37.7 (0.2) | 69.3% (1.7%) | 32.3 (1.5) | 16.4% (1.3%) | 35.8 (0.2) | 62.4% (1.8%) | 18.2 (0.8) | 16.1% (1.3%) |
| Town | City (W) | 470 | 1.5 (0.03) | 39.6 (0.3) | **77.2%** (1.9%) | **46.9** (2.7) | **17.7%** (1.8%) | 37.8 (0.3) | 73.0% (2.1%) | **26.8** (1.8) | **20.4%** (1.9%) |
| City | Rural | **932** | 1.39 (0.02) | 39.6 (0.2) | 85.0% (1.2%) | 43.5 (2.5) | 21.9% (1.4%) | 37.6 (0.2) | 79.8% (1.3%) | 29.4 (1.5) | 21.1% (1.3%) |
| City | Town (O) | 198 | **1.58** (0.04) | 38.9 (0.4) | 79.3% (2.9%) | 36.5 (3.3) | 18.2% (2.7%) | 36.6 (0.3) | 80.8% (2.8%) | 24.1 (3.2) | 17.3% (2.7%) |
| City | City (O) | 457 | 1.31 (0.02) | **40.5** (0.3) | 78.6% (1.9%) | 42.2 (3.6) | 18.2% (1.8%) | **38.6** (0.3) | 76.4% (2.0%) | 26.6 (2.7) | 18.0% (1.8%) |
| City | Town (W) | 214 | 1.45 (0.04) | 38.8 (0.4) | **86.4%** (2.3%) | 47.6 (4.1) | 20.6% (2.8%) | 37.2 (0.4) | **82.2%** (2.6%) | 29.1 (2.3) | 26.7% (3.1%) |
| City | City (W) | 629 | 1.35 (0.02) | 39 (0.2) | 83.4% (1.5%) | **51.6** (2.7) | **27.3%** (1.8%) | 37.1 (0.2) | 82.0% (1.5%) | **34.4** (1.8) | **30.0%** (1.8%) |

[a] Standard errors in parentheses.

[b] (O) denotes town/city closest to household *Hukou* location. (W) denotes town/city closest to parent work location.

[c] The income unit is 1,000 CNY deflated to 2010 (around 115 EUR or 147 USD).

[d] 9-yr. edu.: The compulsory education in China, 6 years of primary school plus 3 years of middle school.

[e] The **highest** value of each indicator in each group (of work location type) is in bold, the lowest in gray.

## 3.3 Schools in Different Locations

Figure 4 shows the regression estimates of the effect of school location on children's word test scores, controlling for lagged test scores[12] and child fixed effects using panel data on children from 2010 to 2022. The dynamic panel coefficients suggest that town and city schools strongly dominate rural schools in terms of transitory effects on children's academic achievement. However, the effects of urban and rural schools are not strictly distinct. The results are similar for math test scores, as shown in Figure 5. For the effects on math scores, city schools are better than town schools, especially for middle school students (ages 12 to 15).

There are several concerns with the reduced-form results above. First, students are not randomly assigned to schools in different locations, and the choice of school location is endogenous to parents' choice of work location. What's more, since most children stay in the same school over time, the effects of schooling on test scores are likely to be cumulative, while the above regression specification only examines the transitory effects of being enrolled in different types of schools for the most recent period. The results without controlling for the lagged dependent variable can be found in Figure A4 and Figure A3, which show a similar pattern.

The motivating data facts in this section show that there is sorting into different work and school locations, and that the effects of schools on children's school outcomes differ across different types of locations. This motivates a structural model to explore how parents migrate, taking into account the costs and benefits of migration as well as the expected gains from children's education, and how they send their children to schools in different locations conditional on the migration decision.

[12]The lagged test scores are from the period $t - 2$, where $t$ refers to the wave, because the CFPS standardized tests are comparable every two waves.

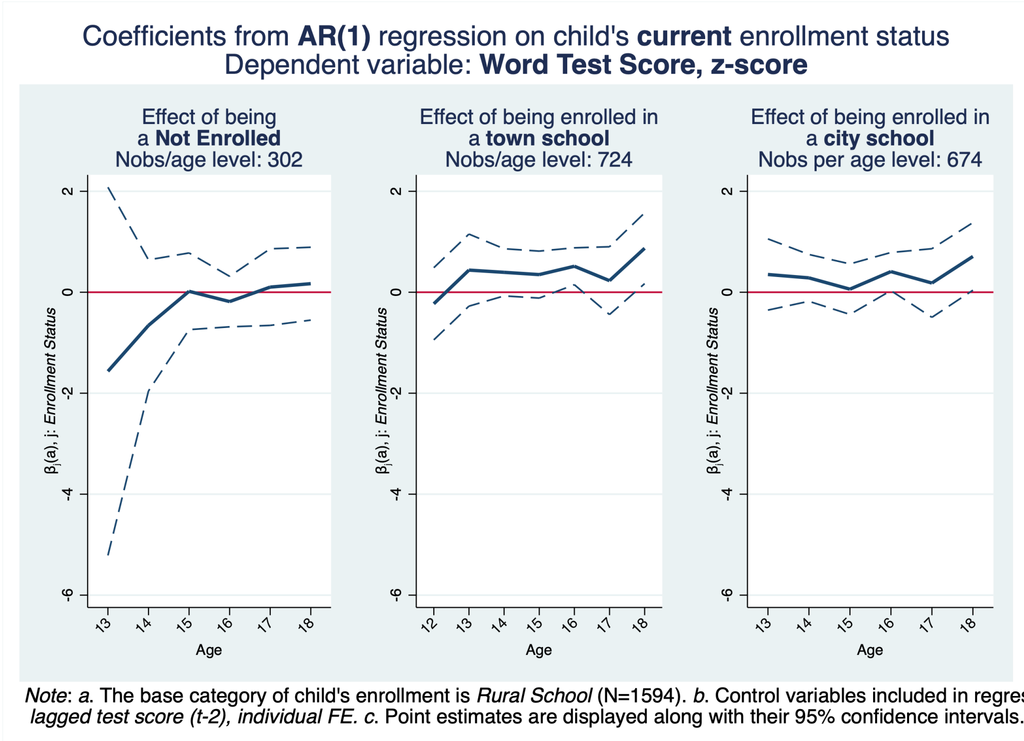



Figure 4: Child's Word Test Score Regression Coefficients

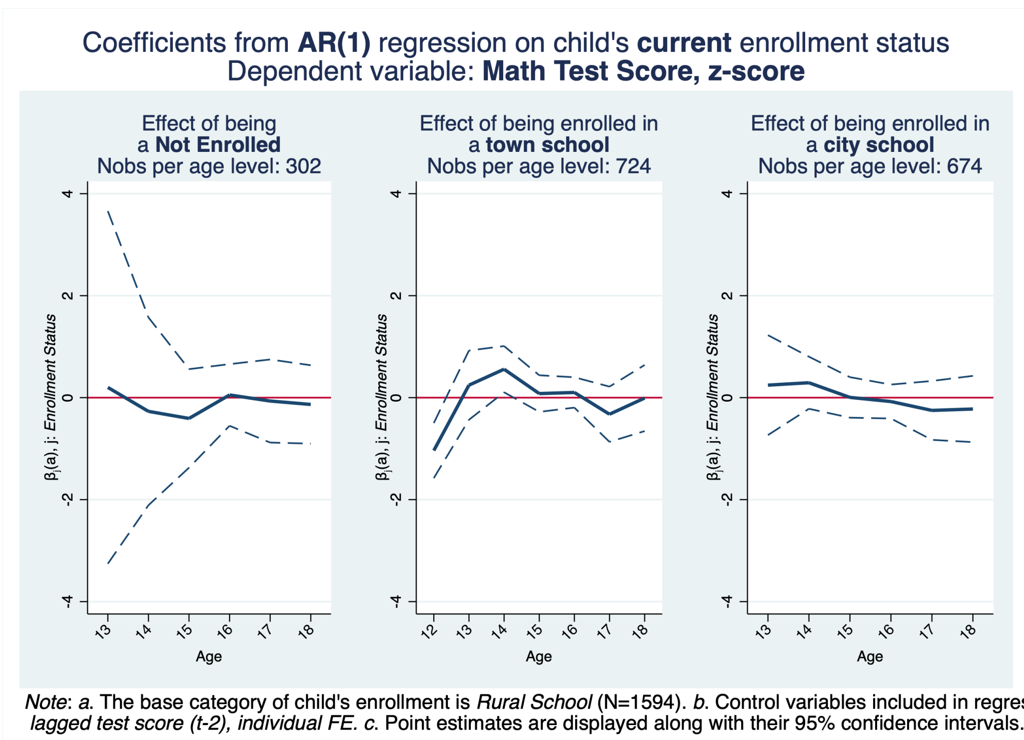



Figure 5: Child's Math Test Score Regression Coefficients

# 4 Model

In this section, I present a nested model of household decisions about parental migration and children's education. This model captures the specifics of the Chinese context, where there is a rapid urbanization process and the *Hukou* system restricts rural-urban migrants' access to local social services, including education, while being general enough to apply to other contexts of household migration under mobility frictions.

The model has two nests: the upper nest is the decision of the parent's work location and the lower nest is the decision of the child's school location. In the household decisions, the active decision maker is assumed to be the rural parents with migration opportunities. Figure 6 shows the tree structure of the model.

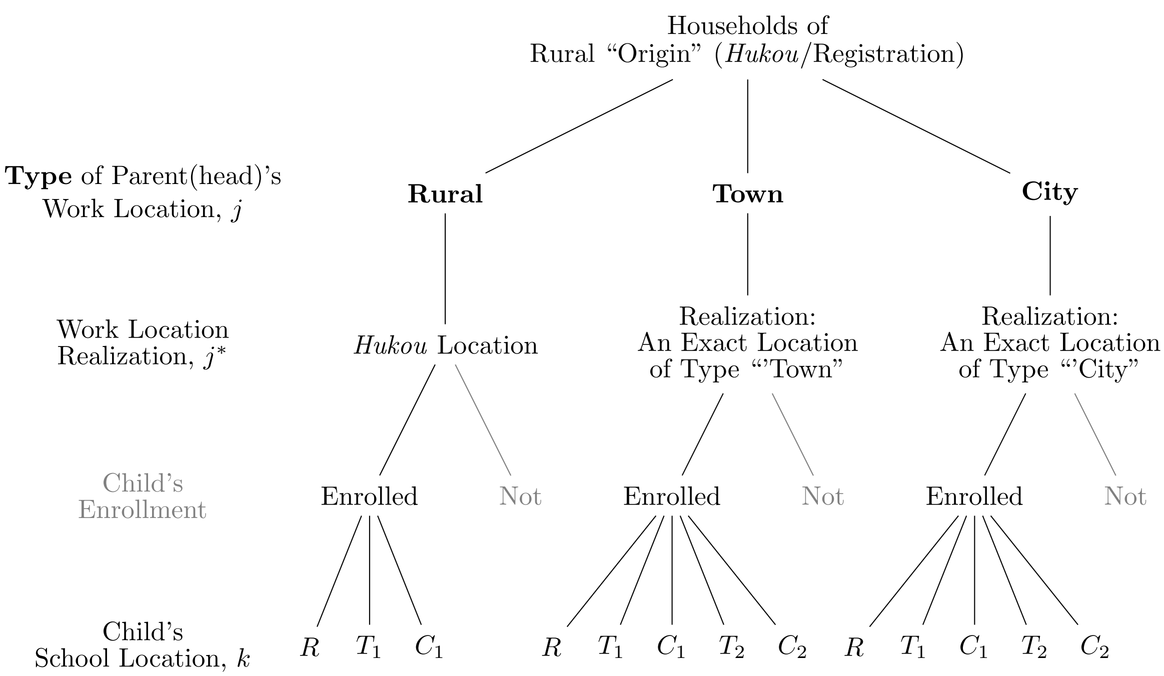


Figure 6: Tree Structure

The extensive margin of the child's education - the child's enrollment - is not discussed in this model. Not enrolled is not a category that can be lumped together with the three school locations because the child can go to different locations when not in school, which is another margin to explore and not the focus of this model. From my data, 72.5% of the out-of-school rural-*Hukou* children stay in rural areas, 16% of them go to towns, and 6.6% of them go to cities. Figure A2 shows the estimates from the dynamic panel of the effect of parental migration and separation on child enrollment, which suggests a zero effect of children brought to the destination by migrant parents and a negative effect of being left behind, both relative to non-migrant rural counterparts.

## 4.1 Working Location Choice

In the upper nest, a household of rural origin (*Hukou*) first decides the type of work location. After the type $j$ is decided, an exact location $j^*$ is realized from the pool of locations in that type. The choice of type can be considered as the worker decides whether to migrate or not, and generally an easier choice (town) or a more difficult choice (city). And once the type of destination is chosen, the random realization is made to reflect the fact that the worker will rely on the link established between his origin and all potential destinations to make the location choice.

The decision on work location for each household is

$$d_1 = j,\ j \in \{Rural,\ Town,\ City\}.$$

And given type $j$, an exact location (county) $j^*$ will be realized as the *Hukou* location if $j = Rural$, and will be a random draw if $j = Town$ or $City$ from the distribution

$$f_i(j^*|j) = \frac{M_{O_i,j^*}}{M_{O_i,j}},$$

where $M_{o,d}$ is the baseline (year 2010) migration stock from location $o$ to location $d$; $O_i$ is the *Hukou* location ($O$ for origin) of individual $i$. Historical settlement patterns capture migration costs (time and distance), bilateral migration networks, and preferences for different locations (Kinnan et al., 2018; Imbert et al., 2022). This historical pattern of migration between locations may reflect the bilateral links established between origin and potential destinations, and may predict future migration patterns, as it indicates migrants' expectations about the future evolution of destination output and labor demand. Using the baseline migration pattern confirms that this variation is not contributed by the decisions of the sampled individuals within the time frame of the survey data (2010-2022), so it is exogenous to the model. When the household chooses the work location type $d_1$, the parents compare the expected location in each type, which has the weighted average characteristic of all locations in that type.

The household's indirect utility of working in location type $j$ is

$$U_j^{(1)} = \gamma_j \cdot x^{(1)} + \sum_{j^*} p_{j^*|j} \cdot (\beta \cdot y_{j^*} + \rho_j \cdot V_{j^*}) + \varepsilon_j^{(1)}$$

where $x^{(1)}$ is a vector of parent demographics and $y_{j^*}$ is a vector of migration benefits and costs. The demographics don't vary between different location realizations, so they don't go into the sum. The costs and benefits of migration are location-specific, and are then included in the utility as weighted averages of the costs and benefits of all locations in the type. The utility is type-specific, not location-specific, which assumes that the parent compares the expected utility of each type to make the decision.

## 4.2 School Location Choice

In the lower nest, the household decides the location of the child's school relative to the household's origin and the parent's workplace $j^*$. The school location decision is denoted by

$$\begin{aligned} d_2 = jk,\ k \in K_j = \{&\text{Rural (R, } \textit{Hukou} \text{ location)}, \\ &\text{Town } (T_1) \text{ or City } (C_1) \text{ closest to } \textit{Hukou} \text{ Location}, \\ &\text{Town } (T_2) \text{ or city } (C_2) \text{ closest to work location } j^*\}, \forall j. \end{aligned}$$

where $K_j$ is the set of school locations $K_j$ under work location $j$, and $jk$ denotes a specific alternative in the lower nest. $K_j$ is the same across all $j$, although for different realizations of $j^*$, $T_2$ and $C_2$ are different. The indirect utility of sending the child to school at location $k$ is

$$U_{j^*k}^{(2)} = \alpha_j \cdot z_{j^*k} + \mu_{jk} \cdot x^{(2)} + \varepsilon_{j^*k}^{(2)} \tag{4.1}$$

where $x^{(2)}$ includes the child's demographic variables, which do not vary across locations, and $z_{j^*k}$ includes the benefits and costs of the child's education, which vary across school locations, these variables are assumed to affect the parent's work location only through their effect on the child.

# 5 Estimation

In the nested structure, the model is estimated backwards in two stages (limited information maximum likelihood estimation, LIML estimation), starting from the lower nest of the school location decision and then incorporating the gains from the lower nest in the upper nest of the work location decision.

## 5.1 Child School Location Choice

For the gains from education, the estimates are obtained by maximizing the log likelihood of a conditional logit model on choosing the school location $jk$, where the log likelihood is given by

$$\ln L_2 = \sum_i \sum_j \sum_{j^*} \sum_k d_{ij^*k} \ln p_{ik|j^*}$$

and the probability of selection is

$$p_{k|j^*} = \frac{\exp\left[\left(\alpha_j \cdot z_{j^*k} + \mu_{jk} \cdot x^{(2)}\right)/\rho_j\right]}{\sum_{l=1}^{K_j^*} \exp\left[(\alpha_j \cdot z_{j^*l} + \mu_{jl} \cdot x^{(2)})/\rho_j\right]}$$

The estimates obtained directly from this stage are $\frac{\hat{\alpha}}{\rho_j}$ and $\frac{\hat{\mu}}{\rho_j}$, which will be combined with the estimates for $\rho_j$ from the next step to get the estimates for $\alpha$ and $\mu$.

### 5.1.1 Costs of Education and Child's Academic Performance

In the estimation, the alternative-specific regressor vector $z$ in the school choice utility (4.1) takes the expected value for each alternative. Educational expenditures $c$ and the child's academic performance $s$ are included in $z$ to capture the costs and benefits of education.

The educational expenditure of the child who attends a school at location $k$ is predicted using

$$\ln c_{kt} = \theta^c_{j(k),a} \cdot a^c_t + \delta^c_{1,k} + \delta^c_{2,t} + \varepsilon^c_{kt},$$

where expenditures are assumed to vary as the children grow older and enter a new stage of education. This age effect is allowed to differ by the type of school location $k$ (rural, town, or city, denoted by $j(k)$) and is treated as non-linear by including age as a set of dummies and then interacting it with $j(k)$. The regression also includes school location fixed effects $\delta^c_{1,k}$ and time fixed effects $\delta^c_{2,t}$.

The child's test scores are predicted using a similar specification:

$$s_{kt} = \theta^s_{j(k),a} \cdot a^s_t + \delta^s_{2,k} + \delta^s_{3,t} + \varepsilon^s_{kt},$$

where age is included as a set of dummies and the nonlinear age effects are assumed to differ by location type $j(k)$, and the school location and time effects are also included. The z-score of the raw test score is used as the dependent variable, and the prediction is done separately for the word test and the math test. The standard deviation score z-score is standardized to the reference population (from the CFPS data) for the child's age and gender, but it may still have an age trend across region and time. Testing the prediction under many specifications confirms the age effect and suggests that gender has almost no effect on the z-score that varies across region or time.

## 5.2 Parent Work Location Choice

In the upper nest, $\hat{\beta}$, $\hat{\gamma}_j$, and $\hat{\rho}_j$ are estimated by maximizing the log likelihood of a conditional logit model on choosing the work location $j$ with log likelihood given by

$$\ln L_1 = \sum_{i=1}^{N} \sum_{j} d_{ij} \ln p_{ij}.$$

The choice probability is

$$p_j = \frac{\exp\left[\gamma_j \cdot x^{(1)} + \sum_{j^*} p_{j^*|j} \cdot (\beta \cdot y_{j^*} + \rho_j \cdot V_{j^*})\right]}{\sum_{m=1}^{J} \exp\left[\gamma_m \cdot x^{(1)} + \sum_{m^*} p_{m^*|m} \cdot (\beta \cdot y_{m^*} + \rho_m \cdot V_{m^*})\right]}$$

The added regressor $V$ is the inclusive value from the lower nest:

$$V_{j^*} = \ln\left\{ \sum_{l=1}^{K^*_j} \exp\left[\left(\alpha_j \cdot z_{j^*l} + \mu_{jl} \cdot x^{(2)}\right)/\rho_j\right] \right\}.$$

and the probability of realizing an exact location $j^*$ from the pool of locations of type $j$ if $j$ is not rural:

$$p_{j^*|j} = \frac{M(O, j^*)}{\sum_{\{\tilde{j}:\,\text{type}(\tilde{j})=j\}} M(O, \tilde{j})}$$

while if $j$ is rural, then $j^*$ will be set as the *Hukou* location. This means that if $j$ is rural, the regressors subscripted by $j$ and $j^*$ take the level of the $Hukou$ location, which is justified by the fact that rural-rural migration is not considered in this model, and by the fact that the within-group discrepancy between different rural locations is assumed to be fully captured by the variation in the socio-economic indicators of rural households. In $p_{j^*|j}$, $O$ is the *Hukou* location of the household and $M$ is the baseline migration stock. For each origin (county-level data are used), a maximum of 6 possible destinations of each type (town or city) were observed in the data at baseline, and almost all origins were observed to have at least three destinations connected with them in terms of historical migration stock. Three potential locations are used to form the pool $\{\tilde{j} : \text{type}(\tilde{j}) = j\}$ for each $j$ equal to town or city. This pool of realizations of $j^*$ under each $j$ of size 3 is origin(*Hukou*)-specific, people from the same origin share the same pool.

### 5.2.1 Costs of Migration and Labor Income Gains from Migration

The costs of migration include higher prices at the destination and institutional constraints on mobility.

To capture the variation in prices at destination, the housing prices reported in each municipality are used. Although it could be argued that total housing costs could be a better measure of the cost of living, while the migrant may reduce housing costs by reducing living space due to a limited budget, the housing price could be a good real measure of the cost of living (Brueckner and Lall (2015)), and compared to food costs, housing costs account for the majority of the total cost of living.

For institutional costs, I use the *Hukou* conversion rate, which is defined as the proportion of migrants who had converted their *Hukou* registration place to the local place by the last wave of the survey:

$$C_{l,\overline{edu}} = \frac{\sum_i \mathbb{1}\{\mathtt{d}_i = l, edu_i = \overline{edu}\} \cdot \mathbb{1}\{\mathtt{hk}_{i,a_0} \neq l\} \cdot \mathbb{1}\{\mathtt{hk}_{i,T} = l\}}{\sum_i \mathbb{1}\{\mathtt{d}_i = l, edu_i = \overline{edu}\} \cdot \mathbb{1}\{\mathtt{hk}_{i,a_0} \neq l\}}$$

The conversion rate is allowed to vary by the educational level of the migrant applicant across location types. This captures the variation in the success rate of the conversion process across educational levels and regions, and reflects the general tendency of Hukou policies to attract talent, but with different intensity across regions.

An alternative measure of mobility restriction in the Chinese context that has been used in recent literature (Khanna et al. (2021); Imbert et al. (2022); Gao et al. (2023)) is the *Hukou* stringency index proposed by Zhang et al., 2019. The index measures the ease of obtaining a local *Hukou* based on the migrant's employment (job and length, contribution to pension system, etc.), educational background (high-tech migrants are more welcome), local investment, and real estate purchase. The more difficult it is to obtain the destination's *Hukou*, the higher the index. The index is highest for the capital of China, followed by the other major cities. The index can take a maximum of two values for each location - one before 2014 and one from and after 2014 - and remains fixed for the duration of each time interval. A drawback of the stringency index in my analysis is that it mostly has variation only for city locations, not for town locations as I have defined them.

The *Hukou* conversion rate has the advantage that it can capture the variation in destination restrictiveness as well as migrants' willingness to convert their *Hukou* status to local, and this helps to estimate preference parameters on the sample of destinations that are less restrictive and have little variation in the stringency index.

The gains from migration come mainly from the urban income premium. To capture this gain, the labor income of rural parents across locations is predicted using the following specification:

$$\ln w_{j^*t} = \theta^w_{1,a} \cdot a^p_t + \theta^w_{2,je} \cdot e^p_i + \delta^w_{1,j^*} + \delta^w_{2,t} + \varepsilon^w_{j^*t}$$

where the dependent variable is the log of the labor income of the parent who chooses location $j^*$ within type $j$, in real terms (1000 CNY, 2010), superscript $^p$ denotes the parent, $a$ is age included as a set of age dummies, and $e$ is educational attainment level. Location and time fixed effects are also included. The return to education is allowed to differ by education level and location type to capture the fact that returns to education would be higher in more developed urban locations and for more educated individuals.

## 5.3 Model Estimates

In this section, I present the model parameter estimates, while the effects on choice probabilities are discussed in the next section in the counterfactual exercises.

Table 3: Alternative-Specific Regressors Estimates from Conditional Logit Regression on School Location Choice.

| | All Origins | | | Origins without Secondary School | |
|---|---|---|---|---|---|
| | [6,12) | [12,15) | [15,18] | [12,15) | [15,18] |
| *School-Location-Specific Variables* | | | | | |
| No. Primary Schools (Work = R) | -0.020 | | | | |
| | (0.025) | | | | |
| No. Primary Schools (Work = T) | -0.007 | | | | |
| | (0.038) | | | | |
| No. Primary Schools (Work = C) | -0.900*** | | | | |
| | (0.146) | | | | |
| No. Secondary Schools (Work = R) | | 0.071 | -0.059 | -0.121 | 0.004 |
| | | (0.089) | (0.063) | (0.256) | (0.184) |
| No. Secondary Schools (Work = T) | | -0.016 | -0.128 | -0.614 | -0.850 |
| | | (0.140) | (0.097) | (1.088) | (0.478) |
| No. Secondary Schools (Work = C) | | -0.869** | -0.309 | -0.349 | -0.239 |
| | | (0.282) | (0.339) | (0.424) | (0.328) |
| Word Score, z (Work = R) | | -0.547*** | -0.234 | -0.619* | -0.672** |
| | | (0.146) | (0.126) | (0.293) | (0.234) |
| Word Score, z (Work = T) | | 0.007 | 0.211 | 0.048 | 0.150 |
| | | (0.163) | (0.143) | (0.326) | (0.261) |
| Word Score, z (Work = C) | | 0.067 | 0.206 | 0.121 | -0.158 |
| | | (0.178) | (0.150) | (0.334) | (0.276) |
| Edu. Expenses (Work = R) | -0.069* | -0.027 | -0.062 | 0.042 | 0.216* |
| | (0.034) | (0.040) | (0.060) | (0.116) | (0.109) |
| Edu. Expenses (Work = T) | -0.002 | -0.002 | -0.084 | 0.013 | 0.156 |
| | (0.036) | (0.043) | (0.063) | (0.119) | (0.112) |
| Edu. Expenses (Work = C) | 0.029 | 0.038 | -0.035 | 0.102 | 0.221* |
| | (0.039) | (0.048) | (0.067) | (0.118) | (0.112) |
| N | 133,484 | 67,613 | 72,163 | 28,600 | 30,784 |
| Log-likelihood | -16918.3 | -8812.6 | -10654.1 | -3692.2 | -4384.3 |

*a.* Cluster(individual level)-robust standard errors in parentheses.
*b.* * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
*c.* Sample: rural households.
*d.* Time variable: two year waves. Data 2010-2022 pooled.
*e.* Test scores are the z-scores adjusted for age and gender.
*f.* Monetary units are in logs and are deflated to CNY 2010.

Table 3 shows the results for the alternative-specific variables from the lower nest. The parameter estimates from the conditional logit regression are informative about the signs of the effects of changing the regressor. The negative coefficients on education expenditure when the parents' place of work is rural suggest that as the expected expenditure for a potential school location increases, this location is chosen less. The magnitude of the coefficients suggests that households are more sensitive to education expenditures when parents work in rural areas, and less sensitive when they are households from origins without a secondary school, where they have no choice but to send the child out of their hometown if they want the child to be enrolled. The negative coefficients on expenditure in all specifications when the place of work is rural suggest a clear tendency for children from households with more limited budgets to be sorted into cheaper, and therefore more likely to be inferior, schools. Coefficients for the individual-specific regressors from the lower nest can be found in tables A3, A4, and A5 in the Appendix.

Table 4 shows the results from the upper nest. The negative coefficients on housing price confirm that households avoid high costs. And although regions with high housing prices tend to be the more restrictive regions, we still observe negative coefficients on the conversion rate, suggesting that settlement restrictions are not effective in controlling migration flows and that they simply cause migrants to concentrate in the most restrictive and congested cities. The effect of income is significantly positive for the subsample of households from an origin without secondary education. The coefficients on the individual-specific variables confirm the selection into migration on the level of parental education and the sorting into different migration destinations on all observed demographic characteristics. Having more children reduces the probability that parents will work outside rural areas, and even more so that they will work in cities.

Table 4: Conditional Logit Regression on Work Location Choice.

| | All Origins | | | Origins without Secondary School | |
|---|---|---|---|---|---|
| | [6,12) | [12,15) | [15,18] | [12,15) | [15,18] |
| *Work-Location-Specific Variables* | | | | | |
| Inclusive Value (Work=R) | 0.628*** | 0.742*** | 0.600*** | 0.806*** | 0.889*** |
| | (0.143) | (0.097) | (0.101) | (0.151) | (0.134) |
| Inclusive Value (Work=T) | 0.075 | 0.057 | 0.566*** | 0.381 | 0.888*** |
| | (0.306) | (0.333) | (0.137) | (0.393) | (0.168) |
| Inclusive Value (Work=C) | 0.748*** | 0.546* | 0.639*** | 0.889** | 0.890*** |
| | (0.136) | (0.216) | (0.161) | (0.304) | (0.172) |
| Income | 0.069 | 0.113 | -0.048 | 0.407** | 0.228 |
| | (0.065) | (0.085) | (0.081) | (0.128) | (0.117) |
| Housing Price | -0.021* | -0.060*** | -0.020 | -0.082** | -0.019 |
| | (0.009) | (0.015) | (0.013) | (0.029) | (0.024) |
| Conversion Rate | -0.906*** | -1.164*** | -1.106*** | -1.171*** | -1.204*** |
| | (0.119) | (0.148) | (0.143) | (0.231) | (0.229) |
| *Work Location: Town* | | | | | |
| Age (Parent) | 0.130 | -0.103 | -0.043 | -0.360*** | -0.201 |
| | (0.080) | (0.062) | (0.078) | (0.105) | (0.120) |
| Age-sq. (Parent) | -0.002 | 0.001 | 0.000 | 0.004** | 0.002 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Completes 9-yr Edu. (Parent) | 0.467*** | 0.555*** | 0.139 | 0.428** | 0.110 |
| | (0.077) | (0.099) | (0.089) | (0.157) | (0.141) |
| No. Children (Parent) | -0.100 | -0.047 | -0.029 | -0.031 | -0.002 |
| | (0.057) | (0.068) | (0.066) | (0.107) | (0.103) |
| Constant | -4.444** | -0.220 | -0.432 | 6.133** | 3.603 |
| | (1.400) | (1.447) | (1.923) | (2.358) | (2.865) |
| *Work Location: City* | | | | | |
| Age (Parent) | 0.602*** | 0.672*** | 0.497** | 0.390 | 0.220 |
| | (0.120) | (0.193) | (0.186) | (0.269) | (0.210) |
| Age-sq. (Parent) | -0.007*** | -0.008*** | -0.005* | -0.004 | -0.002 |
| | (0.002) | (0.002) | (0.002) | (0.003) | (0.002) |
| Completes 9-yr Edu. (Parent) | 1.168*** | 1.402*** | 0.873*** | 1.146*** | 1.228*** |
| | (0.129) | (0.152) | (0.138) | (0.228) | (0.229) |
| No. Children (Parent) | -0.621*** | -0.677*** | -0.337** | -0.609*** | -0.405* |
| | (0.092) | (0.114) | (0.107) | (0.174) | (0.162) |
| Constant | -13.968*** | -16.819*** | -14.126** | -10.693 | -7.248 |
| | (2.299) | (4.160) | (4.436) | (5.926) | (4.987) |
| N | 24,951 | 13,182 | 14,307 | 5,985 | 6,477 |
| Log-likelihood | -6082.7 | -3013.7 | -3387.6 | -1279.9 | -1374.8 |

*a.* Cluster-robust standard errors in parentheses. Clustering is at the individual level.
*b.* * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
*c.* Base category: Working in Rural. *d.* Sample: rural-*Hukou* households.
*e.* Time variable: two year waves. Data 2010-2022 pooled.
*f.* Income is in logs of CNY, house price is in k CNY. Monetary units are deflated to 2010 CNY.

# 6 Counterfactual Exercises

This section presents the results of counterfactual exercises that explore policies that could increase the welfare of rural households with children, or at least achieve the government's existing goals for the rural population (e.g., controlling migration flows and effectively managing the composition of migrants in urban areas) without harming rural children and families.

The effects of counterfactuals in which rural households receive subsidies for education expenditures are evaluated; these policies are typically intended to improve children's welfare by making schooling more affordable and accessible.[13] Although the 9-year compulsory education in China does not charge tuition and other fees, education expenses are not limited to that, and many local rural governments have provided subsidies for the cost of school lunches, boarding fees, commuting fares, and so on. Subsidies for rural children can also be provided at the parents' migration destination. Urban education subsidies have also been implemented by major megacities and many other cities in China to facilitate greater urbanization and assimilation of migrants, and to improve the welfare of migrant children by making urban education more affordable and accessible.

Several counterfactual exercises are then conducted to explore the effects of education subsidies at origin and destination: (1) all education expenditures spent in rural areas are subsidized by 20%; (2) all education expenditures spent in urban areas are subsidized by 15%; (3) all education expenditures spent in urban areas are subsidized by 10%; (4) education expenditures are subsidized by the percentages in the respective areas listed in (1)-(3) only when the migrant parent and child are not separated, that is, when the child is enrolled at the migrant parent's place of work. Scheme (4) is a universal subsidy plan, which is a combination of the first three local subsidy plans on the targeted sample: the rural households. The reduction percentages are set to be different to reflect the reality that prices are higher in towns and highest in cities.

Panel A of Table 5 shows the baseline predicted location choice probabilities using the model estimates and actual data. For the location choice probabilities, parents are more likely to migrate out of the hometown as the child grows up. Panel A of Table 6 shows the baseline predicted probabilities of parent-child separation. If the parent's location of work and the child's location of school don't match, the child is considered separated from the parent. A child is most likely to be separated from its town-migrant parent

[13] The effects of an agricultural income shock and a house price decline are also evaluated, although neither predicts a significant effect.

Table 5: Predicted Choice Probabilities of Parental Migration

| Work Location | Age Group<br>Age [6,12) | <br>Age [12,15) | <br>Age [15,18] |
|---|---|---|---|
| | *A. Baseline* | | |
| Rural | 0.188 | 0.189 | 0.504 |
| Town | 0.756 | 0.697 | 0.326 |
| City | 0.056 | 0.114 | 0.17 |
| | *B. Edu. Expenses Subsidy: Rural Areas (20%)* | | |
| Rural | 0.196 (+4.1pp.) | 0.192 (+1.7pp.) | 0.507 (+0.6pp.) |
| Town | 0.749 (**-0.9pp.**) | 0.695 (**-0.2pp.**) | 0.326 (**-0.3pp.**) |
| City | 0.055 (**-1.9pp.**) | 0.113 (**-1.5pp.**) | 0.167 (**-1.2pp.**) |
| | *C. Edu. Expenses Subsidy: All Towns (15%)* | | |
| Rural | 0.19 (+0.8pp.) | 0.189 (+0.4pp.) | 0.502 (**-0.3pp.**) |
| Town | 0.755 (**-0.1pp.**) | 0.697 (+0.0pp.) | 0.33 (+1.2pp.) |
| City | 0.056 (**-0.7pp.**) | 0.114 (**-0.9pp.**) | 0.167 (**-1.3pp.**) |
| | *D. Edu. Expenses Subsidy: All Cities (10%)* | | |
| Rural | 0.192 (+2.0pp.) | 0.19 (+0.8pp.) | 0.506 (+0.3pp.) |
| Town | 0.753 (**-0.4pp.**) | 0.696 (**-0.1pp.**) | 0.326 (**-0.1pp.**) |
| City | 0.056 (**-1.0pp.**) | 0.114 (**-0.8pp.**) | 0.169 (**-0.6pp.**) |
| | *E. Edu. Expenses Subsidy: Working Location (20%/15%/10%)* | | |
| Rural | 0.196 (+4.0pp.) | 0.192 (+1.6pp.) | 0.508 (+0.8pp.) |
| Town | 0.749 (**-0.9pp.**) | 0.695 (**-0.3pp.**) | 0.325 (**-0.3pp.**) |
| City | 0.055 (**-1.2pp.**) | 0.114 (**-0.8pp.**) | 0.167 (**-1.7pp.**) |

at primary-school age, and most likely to be separated from its city-migrant parent at middle-school age. This is consistent with the sorting of parents migrating to towns and cities and the fact that secondary school seats are more limited than primary school seats in any area, especially in more developed regions.

Panels B through D of Table 5 show the predicted choice probabilities from the model under counterfactual economies in which education spending is subsidized by 20% if the child is enrolled at its rural origin, 15% if the child is enrolled in a town, and 10% if the child is enrolled in a city. Panel E shows the result of a counterfactual that is a combination of the first three. The former three regional subsidy plans will increase the relative attractiveness of schools in the subsidized region, and when we compare across panels, we see that the rural school subsidies have the largest effect on increasing the chance that parents will stay in rural areas. And this suggests that parents do migrate for better educational opportunities for their children, so that higher availability and accessibility of schools at origin reduces migration. If we compare this result with the model estimates for the *Hukou* conversion rate, which indicate that migration frictions are not effective in controlling rural-urban migration flows as intended, we can see that, at

Table 6: Predicted Probabilities of Parent-Child Separation

| Work Location | Age Group: Age [6,12) | Age [12,15) | Age [15,18] |
|---|---|---|---|
| | *A. Baseline* | | |
| Town | 0.448 | 0.414 | 0.174 |
| City | 0.041 | 0.089 | 0.13 |
| | *B. Edu. Expenses Subsidy: Rural Areas (20%)* | | |
| Town | 0.444 (**-0.8pp.**) | 0.414 (**-0.2pp.**) | 0.176 (+1.5pp.) |
| City | 0.04 (**-2.3pp.**) | 0.087 (**-1.9pp.**) | 0.129 (**-0.9pp.**) |
| | *C. Edu. Expenses Subsidy: All Towns (15%)* | | |
| Town | 0.447 (**-0.2pp.**) | 0.414 (0.0pp.) | 0.17 (**-1.8pp.**) |
| City | 0.041 (**-0.9pp.**) | 0.088 (**-1.1pp.**) | 0.129 (**-1.1pp.**) |
| | *D. Edu. Expenses Subsidy: All Cities (10%)* | | |
| Town | 0.446 (**-0.4pp.**) | 0.414 (**-0.1pp.**) | 0.175 (+0.7pp.) |
| City | 0.041 (**-1.1pp.**) | 0.088 (**-0.9pp.**) | 0.13 (**-0.4pp.**) |
| | *E. Edu. Expenses Subsidy: Working Location (20%/15%/10%)* | | |
| Town | 0.443 (**-0.9pp.**) | 0.413 (**-0.3pp.**) | 0.17 (**-2.1pp.**) |
| City | 0.041 (**-1.3pp.**) | 0.088 (**-0.9pp.**) | 0.128 (**-1.6pp.**) |

Table 7: Predicted Vocabulary Test Scores, Z-Score

| School Location | Age Group: Age [6,12) | Age [12,15) | Age [15,18] |
|---|---|---|---|
| | *A. Baseline* | | |
| Rural | 0.027 | 0.024 | 0.024 |
| Town | 0.019 | 0.02 | 0.016 |
| City | 0.02 | 0.021 | 0.015 |
| | *B. Edu. Expenses Subsidy: Rural Areas (20%)* | | |
| Rural | 0.028 (**+2.4%**) | 0.024 (**+0.4%**) | 0.026 (**+6.3%**) |
| Town | 0.019 (-1.1%) | 0.02 (-0.1%) | 0.015 (-3.2%) |
| City | 0.019 (-1.1%) | 0.021 (-0.2%) | 0.015 (-2.9%) |
| | *C. Edu. Expenses Subsidy: All Towns (15%)* | | |
| Rural | 0.027 (-0.2%) | 0.024 (**+0.0%**) | 0.023 (-2.8%) |
| Town | 0.02 (**+0.4%**) | 0.02 (0.0%) | 0.016 (**+5.1%**) |
| City | 0.02 (-0.2%) | 0.021 (**+0.0%**) | 0.015 (-2.6%) |
| | *D. Edu. Expenses Subsidy: All Cities (10%)* | | |
| Rural | 0.028 (**+1.2%**) | 0.024 (**+0.2%**) | 0.025 (**+3.1%**) |
| Town | 0.019 (-0.5%) | 0.02 (-0.1%) | 0.015 (-1.6%) |
| City | 0.019 (-0.5%) | 0.021 (-0.1%) | 0.015 (-1.5%) |
| | *E. Edu. Expenses Subsidy: Working Location (20%/15%/10%)* | | |
| Rural | 0.028 (**+2.5%**) | 0.024 (**+0.8%**) | 0.025 (**+2.4%**) |
| Town | 0.019 (-1.0%) | 0.02 (-0.2%) | 0.016 (-0.1%) |
| City | 0.019 (-1.2%) | 0.021 (-0.5%) | 0.015 (-2.3%) |

least in the short run, education subsidies are more effective in controlling migration flows without harming children – as migration restrictions increase the likelihood of parent-child separation of migrant households and do not reduce migration, while education subsidies help reduce separation, as shown in Table 6.

Panel E of Table 5 shows the largest effects of reducing migration of all the panels. In this counterfactual economy, the relative attractiveness of schools in each region is not as high as in the first three panels, which only subsidize the corresponding region. For example, compared to the counterfactual shown in Panel B, where the relative attractiveness of rural schools is the highest of all because it's the only subsidized region, all regions are subsidized in the counterfactual shown in Panel E, albeit at different intensities, but Panel E still predicts the highest probabilities of staying in rural areas. This confirms that parents migrate for better educational opportunities for their children, since the gains from migration in terms of children's education are lower in C and D, and lowest in E. And this can also be explained by the fact that the marginal effect of subsidies in easing household liquidity constraints is higher for rural stayers. If we compare panel C and panel E, or similarly, panel D and panel E, the relative attractiveness of the city is lower in the panel E counterfactual, so it's more intuitive that panel E predicts a larger magnitude of decline in the choice probabilities of cities.

Comparing the columns of Table 5, we see that among city-migrant parents, those with middle school children are more affected than those with primary school children. This is consistent with the fact that middle school seats are much fewer and more expensive than primary school seats, which motivates households to move out of the rural area, either to find a middle school or to earn more resources to finance the schooling. And we also see that towns are very attractive to rural parents of middle-school-age children, that only universal education subsidies can reduce their migration to towns, and that subsidies in rural areas have very little effect on migration to towns, while subsidies in towns have hardly any effect – towns are no substitute for towns for these migrant parents. For an average rural village, there must be more towns than cities around it for migrants to choose from, and migrants can trade the urban wage premium for less distance to travel by choosing one of those towns over cities. If we also look at the parent-child separation probabilities of town-migrant parents of middle school children shown in Table 6, we can further see that although the rural-urban migration stock remains the same under rural subsidy and city subsidy, the family separation increases in both cases – the parents don't leave the migrant destination, just send their children to the subsidized regions, while the town subsidy decreases the family separation of town-migrant families. Comparing the second columns of Table 5 and Table 6, in contrast to the fact that town-migrant parents are reluctant to return to hometown under the subsidy plans, the decrease in the separation of city-migrant households can be attributed almost entirely to migrant parents returning to hometown, this suggests that city-migrants are more sensitive to liquidity constraints and children's education expenditures.

Comparing the city-migrant parents of primary school children and middle school children in Table 6, we see that the rural subsidy plan is more effective than the other two local subsidy plans, even more effective than the universal subsidy, in terms of reducing family separation, while this is not true for the households of high school children. This can be explained by the large descrepancy and hence low substitutability between rural and urban high schools, which is much larger than the regional difference in compulsory education (primary and middle school).

The results shown in Table 7 complement the above interpretations, the results using the math test are consistent with this table and can be found in the Appendix in Table A8. The town and city rows in Panels B and D can be explained by the fact that city and town schools don't produce different outcomes for children aged 12 to 15, which can be confirmed by the AR(1) results in section 3 and the insignificant coefficients presented in table3, and that the quality of city schooling is not sensitive to spending. In Panel B and Panel C, a local subsidy can increase the word test score of the child in the subsidized region, but in Panel D and Panel E, subsidizing students in cities or universally reduces their academic performance but benefits children in rural areas, further confirming the insensitivity of the quality of city schooling to spending, at least for migrants.

The counterfactual education subsidy exercises discussed in this section identify patterns in how rural households respond to different subsidy schemes through migration and family separation, and how this further affects children's test scores. Rural subsidies are the most effective of all subsidy schemes, including regional subsidies and the universal subsidy, at reducing family separation and improving child outcomes without the cost of causing more migration.

# 7 Conclusion

This paper examines the impact of parental rural-urban migration on children by modeling migration as a household decision and incorporating the decision on the location of the child's school as part of the household's migration decision. Using a nested discrete choice model and estimating it with a panel data of Chinese rural households, the results confirm the selection into migration by socio-economic conditions and sorting into different migration destinations, and show that rural parents migrate for better educational opportunities for their children and a wage premium, avoiding high costs but still concentrating in the most restrictive and congested destinations. The results also show that migration frictions are not effective in controlling migration flows, migrants are concentrated in the most restrictive destinations, which is the opposite of the goal of institutional mobility restrictions.

Counterfactual analyses suggest that education subsidies at the rural origin of migrants are more effective than subsidies at the destination, or even a universal subsidy, in reducing family separation and improving children's school performance. And all education subsidies are more effective than mobility restrictions in controlling migration flows. Not only are mobility restrictions ineffective in correcting the spatial misallocation of labor, as these policies are intended to do, but more importantly, they are detrimental to the welfare of people of rural origin. This sheds light on how policymakers could manage migration: instead of simply restricting mobility and leaving rural households to bear all the costs of lack of local social services and family separation, it might be more effective to identify and target the motivations for migration, an important one being children's education, while not harming the hidden but vulnerable group in labor migration: children.

This paper extends the scope of modeling labor migration to household decisions, allowing for the exploration of more dimensions of child inputs and outcomes than the binary variable of leaving children behind in existing research. The rural-urban division of the model (rural-town-city) is also more comprehensive and realistic to account for regional variations brought about by rapid urbanization. The model is also general enough to be applied to most developing contexts, which are likely to have mobility constraints, complicated and dynamic rural-urban classifications, and large internal migrant populations vulnerable to labor market and macroeconomic shocks.

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# Appendix A Additional Figures and Tables

In this section, I present additional figures and tables that are mentioned in the main text but are not presented in the main text for space reasons, although they are complementary to the main results.

Table A1 shows the sample sizes of the CFPS data across waves by age of the sampled individuals.

Figure A2 plots the estimates for $\beta_j(a_{it})$, $j \in \{\text{migrated with parents, left behind}\}$, from the specification

$$y_{it} = \phi y_{it-1} + \alpha(a_{it}) + \sum_j \beta_j(a_{it}) \cdot D_{jit} + X_{it}\gamma + \delta_{region} + \delta_{mother} + \varepsilon_{it} \quad \text{(Appendix A.2)}$$

along the child's age.

Looking at the left panel of figure A2, we see that the event of *migrating with parents* has no significant effect before about age 15, which is roughly the age at which compulsory schooling ends. Compared to non-migrant children, migrant children living with their parents in urban areas are more likely to attend high school. Because parental characteristics are controlled for in the regressions, this difference in test scores is less likely to be the result of differences in the amount of help their parents provided for their academic performance. Comparing the two panels, left-behind children are generally less likely to attend school before high school age.

Tables A3, A4, and A5 show the coefficients on the individual-specific regressors in the lower nest estimation of the model. The coefficients differ by lower nest alternative,

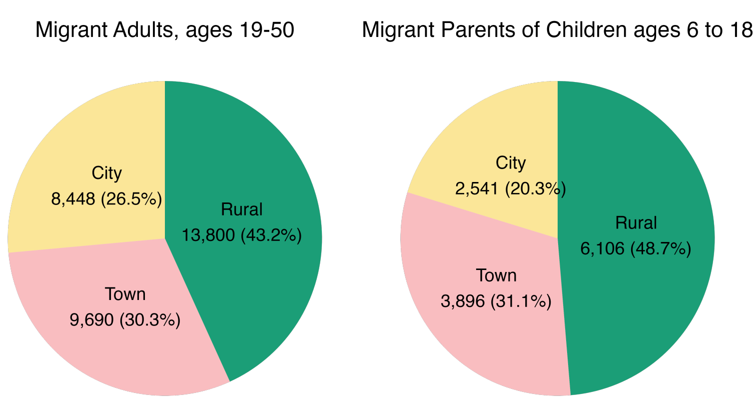


Figure A1: Migrants and Migrant Parents by Type of Destination

Table A1: CFPS Sample sizes

| | Number of sampled individuals aged | | | |
|---|---|---|---|---|
| Wave | [0,5] | [6,14] | [15,18] | [19,50] |
| 2010 | 3,577 | 4,943 | 1,975 | 19,151 |
| 2012 | 3,521 | 4,557 | 2,070 | 21,465 |
| 2014 | 3,596 | 4,479 | 1,930 | 21,332 |
| 2016 | 2,983 | 4,496 | 2,251 | 20,413 |
| 2018 | 2,287 | 4,750 | 1,557 | 18,278 |
| 2020 | 1,673 | 3,995 | 1,234 | 13,930 |
| 2022 | 1,331 | 3,639 | 1,220 | 12,572 |

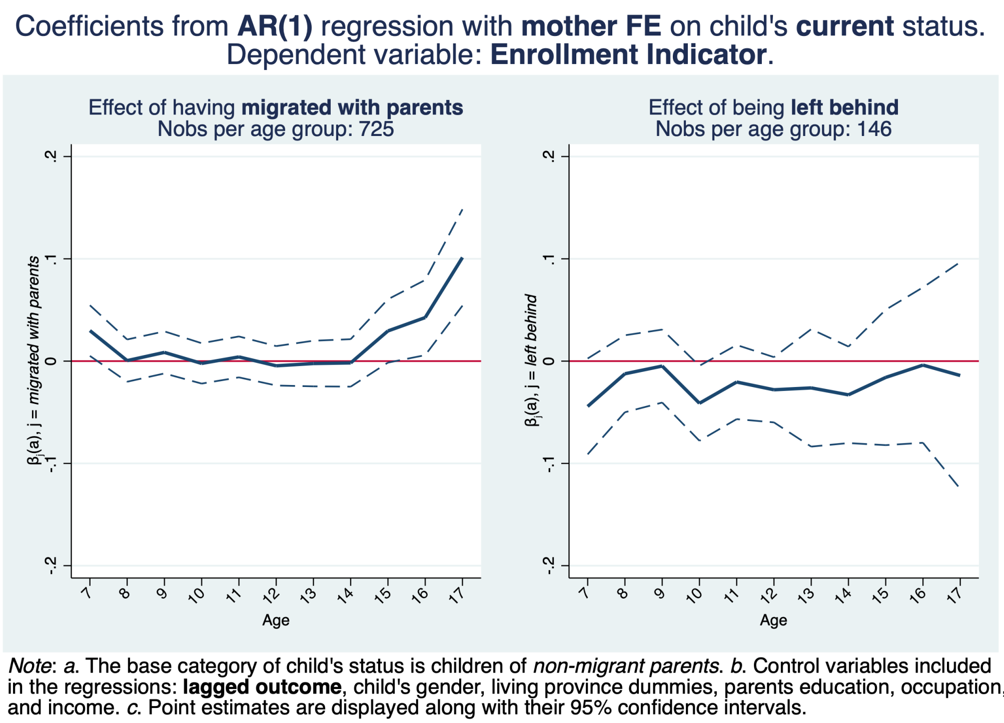


Figure A2: Migration Outcome Gap on Enrollment Rate: Estimates for $\beta_j(a_{it})$ from the dynamic panel (Appendix A.2)

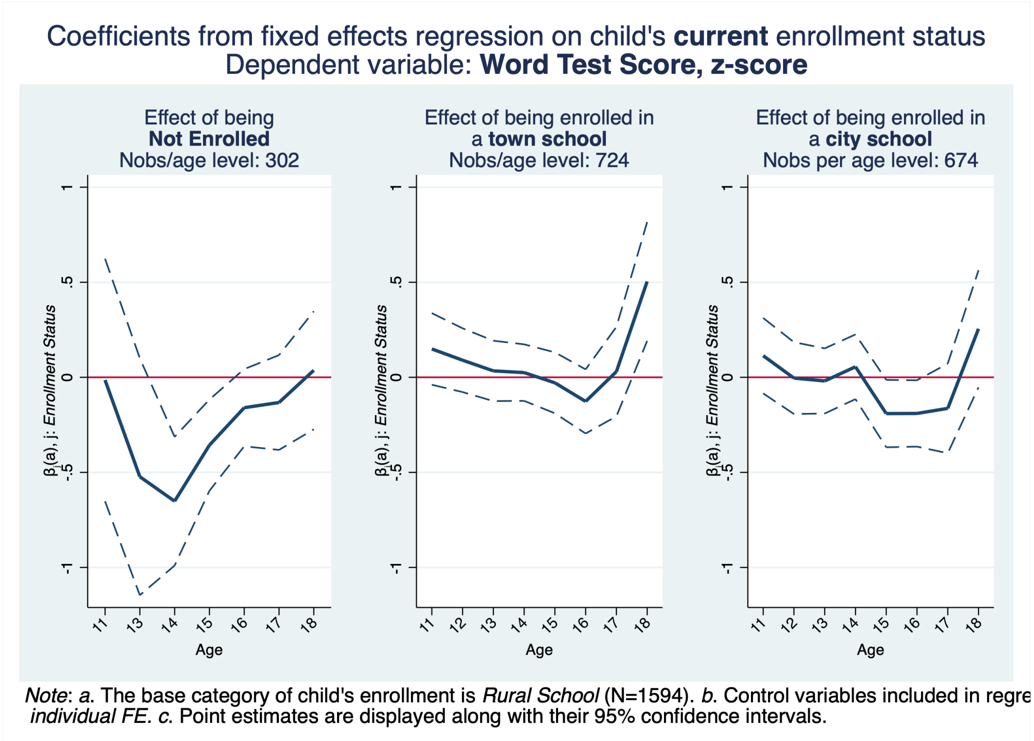


Figure A3: Child's Word Test Score Regression Coefficients

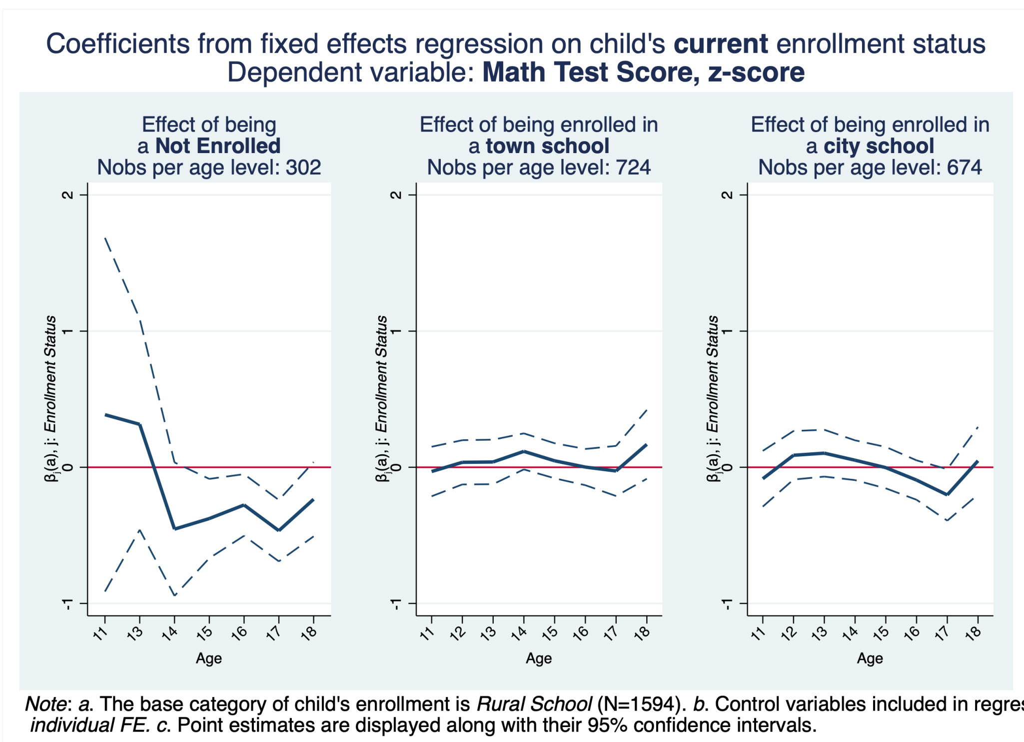


Figure A4: Child's Math Test Score Regression Coefficients which total 13. Marginal effects are not calculated for these regressors because they are reported for each of the thirteen alternatives, so there are 13 $times 13 = 169$ effects for each regressor.

Table A2: Regression for Predicting Alternative-Specific Variables

| | *Dependent Variable* | | | |
|---|---|---|---|---|
| | Income | Edu. Expense | Word Score | Math Score |
| Constant | 5.730*** | 8.744*** | 0.592*** | 0.409*** |
| | (0.198) | (0.283) | (0.107) | (0.112) |
| Year FE | Yes | Yes | Yes | Yes |
| County FE | Yes | Yes | Yes | Yes |
| Age FE | Yes | No | No | No |
| AgeComm FE | No | Yes | Yes | Yes |
| EduComm FE | Yes | No | No | No |
| Observations | 123,881 | 28,135 | 13,709 | 13,218 |
| $R^2$ | 0.224 | 0.367 | 0.277 | 0.232 |

*p<0.05; **p<0.01; ***p<0.001. Standard errors in parentheses.
Time variable: two-year waves. Data 2010 to 2022 pooled.
Test scores are z-scores adjusted for age and gender, observed for children above 10.
Income and expenses are in logs of CNY deflated to 2010.

Table A3: Individual-Specific Regressors Estimates from Conditional Logit Regression on School Location Choice.

| | All Origins | | | Origins without Secondary School | |
|---|---|---|---|---|---|
| | [6,12) | [12,15) | [15,18] | [12,15) | [15,18] |
| Work=R, Edu=T1 | | | | | |
| Age (Child) | 0.135 | 2.191 | 2.132 | 2.399 | 2.104 |
| | (0.273) | (2.657) | (1.182) | (3.524) | (1.733) |
| Age-sq. (Child) | -0.005 | -0.081 | -0.058 | -0.088 | -0.057 |
| | (0.016) | (0.102) | (0.036) | (0.135) | (0.053) |
| Male (Child) | 0.184 | 0.092 | -0.072 | 0.154 | -0.147 |
| | (0.099) | (0.102) | (0.081) | (0.136) | (0.114) |
| Constant | -2.246* | -15.940 | -19.596* | -17.323 | -19.276 |
| | (1.145) | (17.241) | (9.708) | (22.867) | (14.182) |
| Work=R, Edu=C1 | | | | | |
| Age (Child) | -0.439 | -1.879 | 2.340 | 0.685 | 3.752 |
| | (0.401) | (4.226) | (1.455) | (6.315) | (2.218) |
| Age-sq. (Child) | 0.025 | 0.077 | -0.060 | -0.021 | -0.099 |
| | (0.024) | (0.162) | (0.044) | (0.242) | (0.067) |
| Male (Child) | 0.213 | -0.035 | -0.086 | -0.010 | -0.152 |
| | (0.148) | (0.157) | (0.095) | (0.239) | (0.141) |
| Constant | -0.207 | 9.464 | -22.772 | -7.396 | -35.523 |
| | (1.635) | (27.421) | (12.001) | (40.966) | (18.271) |
| N | 133,484 | 67,613 | 72,163 | 28,600 | 30,784 |
| Log-likelihood | -16918.3 | -8812.6 | -10654.1 | -3692.2 | -4384.3 |

*a.* Cluster(individual level)-robust standard errors in parentheses.
*b.* * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
*c.* Base category: Work=R, Edu=R. *d.* Sample: rural households.
*e.* Time variable: two year waves. Data 2010-2022 pooled.

Table A4: Individual-Specific Regressors Estimates from Conditional Logit Regression on School Location Choice.

| | All Origins | | | Origins without Secondary School | |
|---|---|---|---|---|---|
| | [6,12) | [12,15) | [15,18] | [12,15) | [15,18] |
| Work=T, Edu=R | | | | | |
| Age (Child) | -0.008 | 0.035 | -1.935 | -0.550 | -0.724 |
| | (0.192) | (2.834) | (2.190) | (4.966) | (4.613) |
| Age-sq. (Child) | 0.000 | -0.002 | 0.057 | 0.016 | 0.015 |
| | (0.011) | (0.109) | (0.067) | (0.191) | (0.142) |
| Male (Child) | 0.004 | 0.006 | 0.011 | 0.060 | 0.196 |
| | (0.075) | (0.108) | (0.134) | (0.186) | (0.259) |
| Constant | -0.088 | -0.283 | 15.119 | 3.478 | 5.545 |
| | (0.793) | (18.333) | (17.818) | (32.092) | (37.382) |
| Work=T, Edu=T1 | | | | | |
| Age (Child) | -0.014 | -0.024 | 1.418 | 1.465 | 0.934 |
| | (0.300) | (3.651) | (1.766) | (5.915) | (3.152) |
| Age-sq. (Child) | 0.001 | 0.001 | -0.040 | -0.054 | -0.024 |
| | (0.018) | (0.140) | (0.054) | (0.227) | (0.096) |
| Male (Child) | -0.007 | 0.003 | -0.037 | 0.033 | -0.415 |
| | (0.109) | (0.142) | (0.127) | (0.230) | (0.214) |
| Constant | -0.132 | 0.021 | -13.285 | -10.837 | -10.220 |
| | (1.238) | (23.644) | (14.472) | (38.379) | (25.803) |
| Work=T, Edu=C1 | | | | | |
| Age (Child) | -0.060 | 0.179 | -0.733 | -0.226 | -5.313 |
| | (0.723) | (6.897) | (3.134) | (14.178) | (5.195) |
| Age-sq. (Child) | 0.004 | -0.007 | 0.028 | 0.008 | 0.167 |
| | (0.041) | (0.265) | (0.095) | (0.546) | (0.157) |
| Male (Child) | -0.003 | 0.004 | 0.032 | 0.345 | 0.067 |
| | (0.238) | (0.259) | (0.241) | (0.543) | (0.432) |
| Constant | -0.138 | -1.430 | 2.676 | -0.263 | 39.287 |
| | (3.037) | (44.763) | (25.862) | (91.714) | (42.861) |
| Work=T, Edu=T2 | | | | | |
| Age (Child) | -0.015 | 0.398 | 2.383 | 4.047 | 2.467 |
| | (0.334) | (4.309) | (2.326) | (5.310) | (2.896) |
| Age-sq. (Child) | 0.000 | -0.016 | -0.068 | -0.157 | -0.069 |
| | (0.020) | (0.166) | (0.071) | (0.205) | (0.088) |
| Male (Child) | 0.010 | 0.012 | -0.052 | 0.132 | -0.226 |
| | (0.123) | (0.169) | (0.158) | (0.212) | (0.204) |
| Constant | -0.134 | -2.706 | -21.924 | -27.021 | -23.151 |
| | (1.365) | (27.872) | (19.117) | (34.338) | (23.783) |
| Work=T, Edu=C2 | | | | | |
| Age (Child) | -0.022 | 0.133 | -0.350 | 1.943 | -2.017 |
| | (0.447) | (5.895) | (2.505) | (8.786) | (4.189) |
| Age-sq. (Child) | 0.001 | -0.005 | 0.018 | -0.073 | 0.076 |
| | (0.026) | (0.227) | (0.076) | (0.337) | (0.127) |
| Male (Child) | 0.036 | 0.007 | -0.089 | 0.105 | -0.066 |
| | (0.163) | (0.221) | (0.173) | (0.342) | (0.273) |
| Constant | -0.189 | -1.088 | -0.524 | -14.345 | 10.389 |
| | (1.848) | (38.199) | (20.616) | (57.030) | (34.435) |
| N | 133,484 | 67,613 | 72,163 | 28,600 | 30,784 |
| Log-likelihood | -16918.3 | -8812.6 | -10654.1 | -3692.2 | -4384.3 |

*a.* Cluster(individual level)-robust standard errors in parentheses.
*b.* * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
*c.* Base category: Work=R, Edu=R. *d.* Sample: rural households.
*e.* Time variable: two year waves. Data 2010-2022 pooled.

Table A5: Individual-Specific Regressors Estimates from Conditional Logit Regression on School Location Choice.

| | All Origins | | | Origins without Secondary School | |
|---|---|---|---|---|---|
| | [6,12) | [12,15) | [15,18] | [12,15) | [15,18] |
| Work=C, Edu=R | | | | | |
| Age (Child) | -0.002 | 0.397 | 0.296 | -7.293 | -7.388 |
| | (0.298) | (3.832) | (2.082) | (8.556) | (4.627) |
| Age-sq. (Child) | -0.000 | -0.016 | -0.003 | 0.288 | 0.233 |
| | (0.017) | (0.147) | (0.063) | (0.328) | (0.140) |
| Male (Child) | -0.042 | 0.097 | -0.109 | 0.386 | -0.089 |
| | (0.125) | (0.151) | (0.166) | (0.302) | (0.397) |
| Constant | -1.704 | -4.142 | -5.686 | 42.416 | 55.225 |
| | (1.264) | (24.830) | (17.079) | (55.483) | (37.947) |
| Work=C, Edu=T1 | | | | | |
| Age (Child) | 0.278 | 4.119 | 2.408 | 17.693 | 9.205 |
| | (0.716) | (7.272) | (5.123) | (11.746) | (7.359) |
| Age-sq. (Child) | -0.010 | -0.162 | -0.070 | -0.680 | -0.274 |
| | (0.041) | (0.281) | (0.156) | (0.452) | (0.225) |
| Male (Child) | 0.279 | 0.108 | -0.341 | -0.440 | -1.079* |
| | (0.245) | (0.276) | (0.327) | (0.475) | (0.527) |
| Constant | -5.244 | -28.639 | -23.228 | -118.682 | -79.998 |
| | (3.017) | (46.972) | (41.852) | (76.208) | (60.070) |
| Work=C, Edu=C1 | | | | | |
| Age (Child) | -0.456 | 7.641 | 3.803 | 6.161 | 2.425 |
| | (0.459) | (5.105) | (2.727) | (8.960) | (4.826) |
| Age-sq. (Child) | 0.030 | -0.294 | -0.107 | -0.239 | -0.059 |
| | (0.027) | (0.196) | (0.083) | (0.345) | (0.145) |
| Male (Child) | -0.046 | 0.001 | -0.057 | -0.414 | 0.048 |
| | (0.183) | (0.203) | (0.197) | (0.347) | (0.332) |
| Constant | -1.346 | -51.644 | -35.303 | -42.859 | -26.453 |
| | (1.915) | (33.123) | (22.440) | (58.047) | (39.927) |
| Work=C, Edu=T2 | | | | | |
| Age (Child) | 0.492 | 6.630 | 2.234 | 19.858 | -0.340 |
| | (0.613) | (8.188) | (4.635) | (11.198) | (5.680) |
| Age-sq. (Child) | -0.029 | -0.261 | -0.064 | -0.779 | 0.013 |
| | (0.036) | (0.316) | (0.140) | (0.434) | (0.172) |
| Male (Child) | 0.387 | 0.214 | -0.142 | 0.774 | -0.219 |
| | (0.216) | (0.316) | (0.308) | (0.446) | (0.372) |
| Constant | -5.524* | -44.760 | -22.011 | -130.489 | -0.979 |
| | (2.547) | (52.850) | (38.199) | (72.094) | (46.773) |
| Work=C, Edu=C2 | | | | | |
| Age (Child) | -0.834* | 3.276 | 3.939 | 6.688 | 4.500 |
| | (0.347) | (4.811) | (2.618) | (7.283) | (4.001) |
| Age-sq. (Child) | 0.044* | -0.130 | -0.112 | -0.265 | -0.127 |
| | (0.020) | (0.185) | (0.079) | (0.281) | (0.121) |
| Male (Child) | 0.194 | 0.148 | -0.009 | 0.383 | -0.138 |
| | (0.138) | (0.194) | (0.199) | (0.287) | (0.299) |
| Constant | 1.522 | -22.569 | -36.177 | -45.275 | -41.981 |
| | (1.410) | (31.116) | (21.571) | (47.002) | (32.982) |
| N | 133,484 | 67,613 | 72,163 | 28,600 | 30,784 |
| Log-likelihood | -16918.3 | -8812.6 | -10654.1 | -3692.2 | -4384.3 |

*a.* Cluster(individual level)-robust standard errors in parentheses.
*b.* * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
*c.* Base category: Work=R, Edu=R. *d.* Sample: rural households.
*e.* Time variable: two year waves. Data 2010-2022 pooled.

Table A6: Choice Probabilities: Nested Choices

| Work Location | School Location | Age Group | | |
|---|---|---|---|---|
| | | Age [6,12) | Age [12,15) | Age [15,18] |
| | | *A. Actual* | | |
| Rural | R | 0.547 | 0.532 | 0.373 |
| | T1 | 0.063 | 0.105 | 0.196 |
| | C1 | 0.024 | 0.038 | 0.12 |
| Town | R | 0.127 | 0.093 | 0.052 |
| | T1 | 0.053 | 0.053 | 0.067 |
| | C1 | 0.009 | 0.012 | 0.017 |
| | T2 | 0.038 | 0.032 | 0.038 |
| | C2 | 0.02 | 0.017 | 0.032 |
| City | R | 0.046 | 0.047 | 0.039 |
| | T1 | 0.009 | 0.012 | 0.008 |
| | C1 | 0.019 | 0.023 | 0.025 |
| | T2 | 0.012 | 0.009 | 0.008 |
| | C2 | 0.034 | 0.027 | 0.025 |
| | | *B. Baseline Model Prediction* | | |
| Rural | R | 0.135 | 0.131 | 0.232 |
| | T1 | 0.034 | 0.039 | 0.157 |
| | C1 | 0.019 | 0.018 | 0.115 |
| Town | R | 0.167 | 0.148 | 0.076 |
| | T1 | 0.156 | 0.143 | 0.089 |
| | C1 | 0.136 | 0.132 | 0.04 |
| | T2 | 0.152 | 0.139 | 0.064 |
| | C2 | 0.145 | 0.134 | 0.057 |
| City | R | 0.019 | 0.035 | 0.052 |
| | T1 | 0.006 | 0.016 | 0.019 |
| | C1 | 0.01 | 0.024 | 0.04 |
| | T2 | 0.007 | 0.014 | 0.02 |
| | C2 | 0.015 | 0.026 | 0.039 |

Table A7: Predicted Choice Probabilities: Nested Choices

| Work Location | School Location | Age [6,12) | Age [12,15) | Age [15,18] |
|---|---|---|---|---|
| | | *C. Edu. Expenses Subsidy: Rural Areas (20%)* | | |
| Rural | R | 0.143 (+6.0pp.) | 0.135 (+2.5pp.) | 0.241 (+3.8pp.) |
| | T1 | 0.034 (**-0.9pp.**) | 0.039 (**-0.3pp.**) | 0.154 (**-2.2pp.**) |
| | C1 | 0.019 (**-0.9pp.**) | 0.018 (**-0.3pp.**) | 0.112 (**-2.1pp.**) |
| Town | R | 0.166 (**-0.7pp.**) | 0.148 (**-0.1pp.**) | 0.081 (+6.2pp.) |
| | T1 | 0.155 (**-0.9pp.**) | 0.143 (**-0.2pp.**) | 0.087 (**-2.3pp.**) |
| | C1 | 0.135 (**-0.9pp.**) | 0.132 (**-0.2pp.**) | 0.039 (**-2.3pp.**) |
| | T2 | 0.151 (**-0.9pp.**) | 0.139 (**-0.2pp.**) | 0.063 (**-2.3pp.**) |
| | C2 | 0.143 (**-0.9pp.**) | 0.134 (**-0.2pp.**) | 0.056 (**-2.2pp.**) |
| City | R | 0.018 (**-3.9pp.**) | 0.033 (**-4.4pp.**) | 0.053 (+1.3pp.) |
| | T1 | 0.006 (**-0.9pp.**) | 0.016 (**-0.2pp.**) | 0.018 (**-2.3pp.**) |
| | C1 | 0.01 (**-0.9pp.**) | 0.024 (**-0.2pp.**) | 0.039 (**-2.3pp.**) |
| | T2 | 0.007 (**-0.9pp.**) | 0.014 (**-0.2pp.**) | 0.019 (**-2.3pp.**) |
| | C2 | 0.015 (**-0.9pp.**) | 0.026 (**-0.2pp.**) | 0.039 (**-2.3pp.**) |
| | | *D. Edu. Expenses Subsidy: All Towns (15%)* | | |
| Rural | R | 0.135 (**-0.2pp.**) | 0.131 (0.0pp.) | 0.228 (**-1.8pp.**) |
| | T1 | 0.036 (+5.1pp.) | 0.04 (+2.1pp.) | 0.162 (+2.8pp.) |
| | C1 | 0.019 (**-0.2pp.**) | 0.018 (0.0pp.) | 0.112 (**-1.8pp.**) |
| Town | R | 0.166 (**-0.2pp.**) | 0.148 (0.0pp.) | 0.075 (**-1.8pp.**) |
| | T1 | 0.156 (0.0pp.) | 0.143 (+0.1pp.) | 0.093 (+4.7pp.) |
| | C1 | 0.136 (**-0.2pp.**) | 0.132 (0.0pp.) | 0.039 (**-1.8pp.**) |
| | T2 | 0.152 (0.0pp.) | 0.139 (+0.1pp.) | 0.067 (+4.6pp.) |
| | C2 | 0.145 (**-0.2pp.**) | 0.134 (0.0pp.) | 0.056 (**-1.8pp.**) |
| City | R | 0.019 (**-0.2pp.**) | 0.035 (0.0pp.) | 0.051 (**-1.9pp.**) |
| | T1 | 0.006 (**-2.5pp.**) | 0.016 (**-3.2pp.**) | 0.019 (+0.9pp.) |
| | C1 | 0.01 (**-0.2pp.**) | 0.024 (0.0pp.) | 0.039 (**-1.9pp.**) |
| | T2 | 0.007 (**-2.5pp.**) | 0.014 (**-3.2pp.**) | 0.02 (+0.9pp.) |
| | C2 | 0.015 (**-0.2pp.**) | 0.026 (0.0pp.) | 0.039 (**-1.9pp.**) |
| | | *E. Edu. Expenses Subsidy: All Cities (10%)* | | |
| Rural | R | 0.139 (+3.0pp.) | 0.133 (+1.3pp.) | 0.237 (+1.9pp.) |
| | T1 | 0.034 (**-0.4pp.**) | 0.039 (**-0.1pp.**) | 0.156 (**-1.1pp.**) |
| | C1 | 0.019 (**-0.4pp.**) | 0.018 (**-0.1pp.**) | 0.113 (**-1.1pp.**) |
| Town | R | 0.166 (**-0.3pp.**) | 0.148 (0.0pp.) | 0.079 (+3.1pp.) |
| | T1 | 0.155 (**-0.5pp.**) | 0.143 (**-0.1pp.**) | 0.088 (**-1.1pp.**) |
| | C1 | 0.135 (**-0.5pp.**) | 0.132 (**-0.1pp.**) | 0.04 (**-1.1pp.**) |
| | T2 | 0.151 (**-0.5pp.**) | 0.139 (**-0.1pp.**) | 0.064 (**-1.1pp.**) |
| | C2 | 0.144 (**-0.5pp.**) | 0.134 (**-0.1pp.**) | 0.056 (**-1.1pp.**) |
| City | R | 0.018 (**-2.0pp.**) | 0.034 (**-2.2pp.**) | 0.052 (+0.7pp.) |
| | T1 | 0.006 (**-0.5pp.**) | 0.016 (**-0.1pp.**) | 0.018 (**-1.2pp.**) |
| | C1 | 0.01 (**-0.5pp.**) | 0.024 (**-0.1pp.**) | 0.039 (**-1.1pp.**) |
| | T2 | 0.007 (**-0.5pp.**) | 0.014 (**-0.1pp.**) | 0.02 (**-1.2pp.**) |
| | C2 | 0.015 (**-0.5pp.**) | 0.026 (**-0.1pp.**) | 0.039 (**-1.1pp.**) |
| | | *F. Edu. Expenses Subsidy: Working Location (20%/15%/10%)* | | |
| Rural | R | 0.143 (+6.0pp.) | 0.135 (+2.4pp.) | 0.241 (+4.0pp.) |
| | T1 | 0.034 (**-0.9pp.**) | 0.039 (**-0.3pp.**) | 0.154 (**-2.0pp.**) |
| | C1 | 0.019 (**-0.9pp.**) | 0.018 (**-0.3pp.**) | 0.112 (**-2.0pp.**) |
| Town | R | 0.165 (**-0.9pp.**) | 0.147 (**-0.3pp.**) | 0.075 (**-2.1pp.**) |
| | T1 | 0.155 (**-0.8pp.**) | 0.143 (**-0.2pp.**) | 0.092 (+4.4pp.) |
| | C1 | 0.135 (**-0.9pp.**) | 0.132 (**-0.3pp.**) | 0.039 (**-2.1pp.**) |
| | T2 | 0.151 (**-0.9pp.**) | 0.139 (**-0.3pp.**) | 0.063 (**-2.1pp.**) |
| | C2 | 0.143 (**-0.9pp.**) | 0.134 (**-0.3pp.**) | 0.056 (**-2.0pp.**) |
| City | R | 0.018 (**-1.0pp.**) | 0.035 (**-0.3pp.**) | 0.051 (**-2.1pp.**) |
| | T1 | 0.006 (**-1.0pp.**) | 0.016 (**-0.3pp.**) | 0.018 (**-2.1pp.**) |
| | C1 | 0.01 (**-2.5pp.**) | 0.023 (**-2.4pp.**) | 0.039 (**-0.3pp.**) |
| | T2 | 0.007 (**-1.0pp.**) | 0.014 (**-0.3pp.**) | 0.019 (**-2.1pp.**) |
| | C2 | 0.015 (**-1.0pp.**) | 0.026 (**-0.3pp.**) | 0.039 (**-2.1pp.**) |

Table A8: Predicted Math Test Scores, Z-Score

| School Location | Age Group | | |
|---|---|---|---|
| | Age [6,12) | Age [12,15) | Age [15,18) |
| *A. Baseline* | | | |
| Rural | 0.054 | 0.051 | 0.058 |
| Town | 0.038 | 0.036 | 0.035 |
| City | 0.035 | 0.034 | 0.029 |
| *B. Edu. Expenses Subsidy: Rural Areas (20%)* | | | |
| Rural | 0.055 (**+2.0%**) | 0.051 (**+0.6%**) | 0.061 (**+4.0%**) |
| Town | 0.038 (-0.9%) | 0.036 (-0.3%) | 0.035 (-2.3%) |
| City | 0.035 (-0.9%) | 0.034 (-0.3%) | 0.029 (-2.2%) |
| *C. Edu. Expenses Subsidy: All Towns (15%)* | | | |
| Rural | 0.054 (-0.2%) | 0.051 (0.0%) | 0.057 (-1.8%) |
| Town | 0.038 (**+0.4%**) | 0.036 (**+0.0%**) | 0.037 (**+3.4%**) |
| City | 0.035 (-0.2%) | 0.034 (0.0%) | 0.029 (-1.8%) |
| *D. Edu. Expenses Subsidy: All Cities (10%)* | | | |
| Rural | 0.054 (**+1.0%**) | 0.051 (**+0.3%**) | 0.059 (**+2.0%**) |
| Town | 0.038 (-0.5%) | 0.036 (-0.1%) | 0.035 (-1.1%) |
| City | 0.035 (-0.5%) | 0.034 (-0.1%) | 0.029 (-1.1%) |
| *E. Edu. Expenses Subsidy: Working Location (20%/15%/10%)* | | | |
| Rural | 0.055 (**+2.0%**) | 0.051 (**+0.9%**) | 0.059 (**+1.9%**) |
| Town | 0.038 (-0.9%) | 0.036 (-0.3%) | 0.035 (-0.4%) |
| City | 0.035 (-1.0%) | 0.034 (-0.5%) | 0.029 (-1.8%) |

# Appendix B Alternative Counterfactual Exercises

## Appendix B.1 House Price Drop

Housing costs are one of the major concerns of migrant settlement, and there is a two-way relationship between housing prices and migration, given the dual nature of housing as both a consumption good and an asset (Garriga et al., 2023). Although the Chinese government doesn't have direct control over housing prices, it can influence the housing market through land supply, mortgage rates, and other policies. Since 2020, China's housing price index has been declining (Rogoff and Yang, 2021; Liu and Tang, 2021), with the decline more pronounced in non-mega cities. The official figures (National Bureau of Statistics of China, 2024) show that in September 2024, the new house price index has decreased by 4.6% - 10.3% in major cities, and the existing house price index has decreased by 7.6% - 12% in major cities. To capture this fact and to study its impact on rural households, a counterfactual exercise of house price decline is conducted. The house price decline is assumed to be 10% in cities and 15% in towns, which is in line with the recent trend.

The predicted choice probabilities from the model under this counterfactual economy are almost indistinguishable from the baseline (tables are all zeros and are omitted). And it also confirm that, even with this substantial nationwide drop in house prices, the effects on relocation are relatively small in magnitude compared to the effects of tuition subsidies. And this result is also true for parent-child separation and test scores. One possible explanation is that the homeownership rate among rural-urban migrants is 7.5% (China 1% Population Survey 2005), so while the rental price is also affected by house price volatility, this effect is limited for the low homeownership sample. Although small in magnitude, the direction of the effects is consistent across the post-primary age groups, telling us that under this general house price decline, city destinations become relatively more attractive than town destinations, while some of the migrants who leave towns choose to return to rural areas as the value of migration declines.

## Appendix B.2 Agricultural Income Shock

Agricultural income shock is an important source of labor demand shock at the origin of rural workers with migration opportunities. A negative agricultural income shock in response to unexpected weather conditions reduces the opportunity cost of emmigration, but it also tightens the household budget constraint, which makes the overall effect ambiguous, although it's confirmed by the literature that in the practice of international migration from the developing to the developed, the overall income elasticity of migration is positive (Bazzi, 2017). And the tightened budget constraint is more likely to be associated with parent-child separation: migration is motivated by the reduction in income, but the probability that the household can only afford the migration costs of migrant workers is higher compared to when liquidity constraints are not tightened.

The negative agricultural income shock is assumed to be 20% to mimic several regional natural disasters that have occurred in recent years. The model's predicted choice probabilities under this counterfactual economy are almost indistinguishable from the baseline, so the tables of all zeros are omitted here. This is possible because those most affected by the negative shock are the most vulnerable group with the fewest opportunities to migrate, thus reducing the magnitude of the overall effect.