Parental Rural-Urban Migration and Child Education

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Abstract

Household migration involves both parental and child location choices, which raises more issues of selectivity and endogeneity. Sending children to different locations determines the quality of schooling and parent-child separation. A nested discrete choice model is developed that incorporates the expected returns to children's education as part of the parents' migration decision. Estimation results using panel data of Chinese rural households show that the impact of parental internal migration on children's education differs by children's stage of education. Policies on the destination side of migration have the greatest impact on households with primary school-age children, while parents of middle school-age children are the group most motivated to migrate for better educational opportunities for their children. And high school-age children are the group most sensitive to budget constraints, with parents having the lowest substitution between education and migration resources within the household budget. The results also suggest that migration frictions are not effective in controlling rural-urban migration flows as intended.

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

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

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1 Introduction

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 policy makers. Governments in less developed regions were much more likely (78 percent) than those in more developed regions (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.

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 they 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 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 living with their parents.

This paper argues that mobility restrictions are not only ineffective in correcting the spatial misallocation of labor, as these policies are intended to do, but more importantly that they are detrimental to the welfare of people of rural origin, especially the children

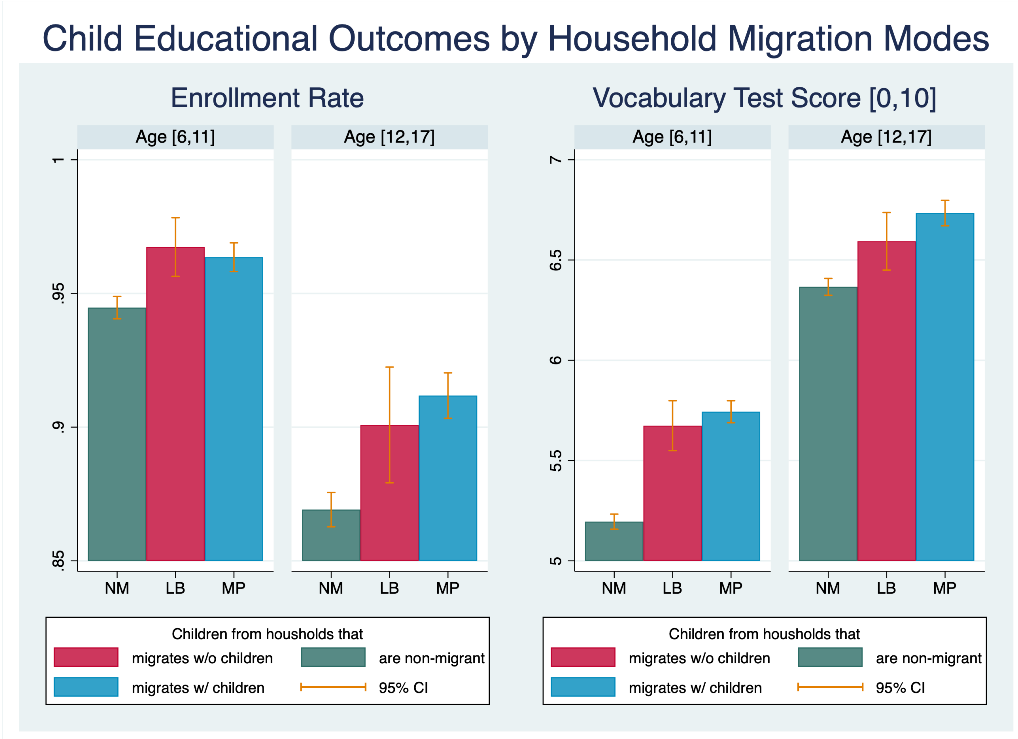


Figure 1: Comparison of Child Educational Outcomes by Group

Data Source: CFPS 2010-2020.

of migrant workers. To fully explore the welfare effects of migration restrictions, 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 do mobility restrictions affect these decisions, 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 cities[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,

[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 cities tend to be more attractive at the same time (Zhang et al., 2020).

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 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 results of counterfactual exercises suggest that settlement restrictions are not effective in controlling migration flows, they just concentrate migrants in the most restrictive and congested cities, and a sizable drop in house prices at destination has little effect on child welfare because settlement is restricted for migrants and they are less sensitive to housing. Education subsidies at origin and destination have different effects, and the pattern of effects, the substitution between education resources and migration resources, also differs across age groups. In terms of education expenditure, primary school age children are more affected at parents' migration destination, parents of middle school age children have the highest motive to translate resources between migration and education, while high school age children are more sensitive to budget constraint, being the most sensitive group to be affected at origin.

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 Background

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 by 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 eligibility criteria for urban Hukou status in large cities. According to my data constructed from *China Family Panel Studies* (CFPS, explained in section 3), waves 2010-2022, only 56.7% of the rural parents (the parents of ever rural Hukou holder children) have completed middle school (the compulsory education in China). As a result, they are unable to access basic local social services such as health care and education for 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 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 the 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

[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 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.

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 the food supply was still tied to a household's place of registration and there were high costs of commodity circulation, the grain production of a city determined the population capacity of the city and was used by the government to decide the *Hukou* registration stringency. Zhang et al. (2020) then suggests the use of level of grain reserve before 2000 as an instrument for migration.

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[5] I restrict my sample to children with rural *Hukou* and their households[6] 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 attends school in an urban place if children and works in an urban place if adults, is registered with a rural *Hukou*, and is observed in my data[7] who has moved across counties. Most literature in this context

[5]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 of 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.

[6]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.

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

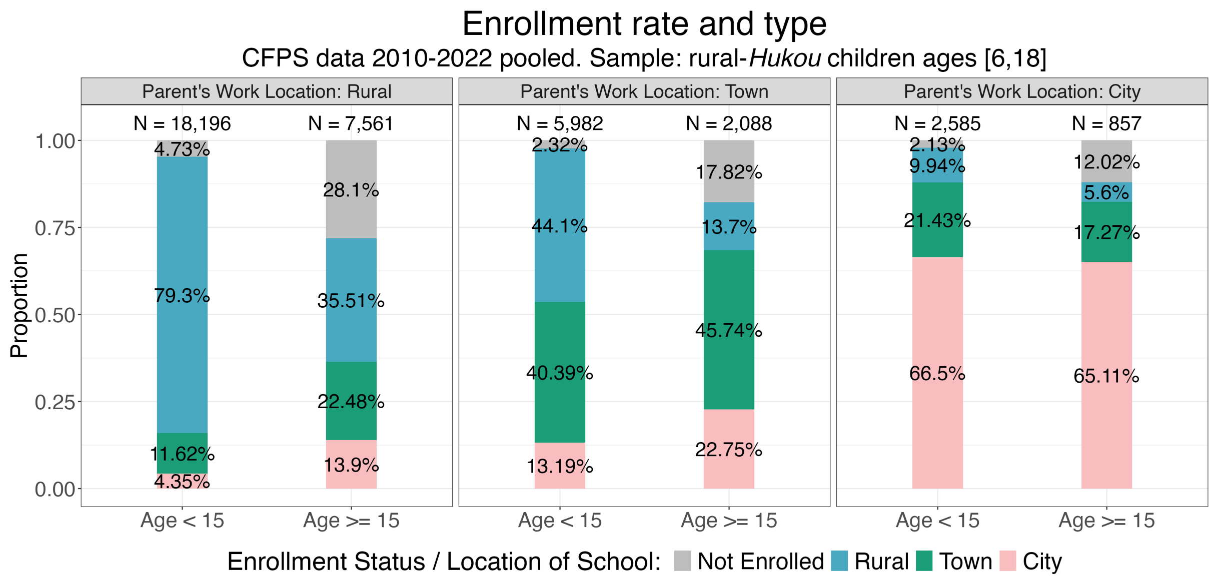
Table 1: Descriptive statistics of enrolled children aged [6,18]

Parent Work Location	Child School Location	Count (Share)	Age	Word Score, Z-Score	Math Score, Z-Score	Edu. Expenses
Rural	Rural	2,519 (77.05%)	10.93 (0.02)	-0.09 (0.01)	-0.1 (0.01)	0.7 (0.02)
Rural	Town (O)	517 (15.82%)	13.29 (0.06)	0.07 (0.02)	0.2 (0.02)	2.17 (0.07)
Rural	City (O)	233 (7.13%)	14.07 (0.09)	0.02 (0.03)	0.14 (0.03)	3.64 (0.17)
Town	Rural	511 (47.25%)	10.54 (0.05)	0.08 (0.03)	-0.06 (0.03)	1 (0.06)
Town	Town (O)	258 (23.83%)	11.83 (0.09)	0.14 (0.03)	0.17 (0.03)	1.44 (0.08)
Town	City (O)	49 (4.53%)	12.55 (0.2)	0.43 (0.07)	0.31 (0.07)	2.82 (0.39)
Town	Town (W)	171 (15.77%)	11.65 (0.11)	0.24 (0.05)	0.27 (0.05)	1.63 (0.11)
Town	City (W)	93 (8.61%)	12.59 (0.16)	0.34 (0.07)	0.3 (0.07)	4.17 (0.29)
City	Rural	187 (39.73%)	11.46 (0.1)	0.32 (0.04)	0.16 (0.04)	2.48 (0.21)
City	Town (O)	45 (9.54%)	11.72 (0.19)	0.31 (0.1)	0.18 (0.1)	2.04 (0.27)
City	City (O)	79 (16.90%)	12.14 (0.15)	0.25 (0.06)	0.25 (0.05)	2.77 (0.35)
City	Town (W)	44 (9.30%)	11.14 (0.2)	-0.06 (0.19)	0.58 (0.12)	2.42 (0.27)
City	City (W)	115 (24.53%)	11.03 (0.13)	0.24 (0.07)	0.23 (0.06)	3.69 (0.3)

[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.

defines the migrant only based on the separation of *Hukou* place of registration and place of residence, I add the cross-county[8] movement variable to the definition, so that the rural-urban migrants within commuting distance are excluded from the sample.

For the rural-urban division, I divide the 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. This type is reported by the CFPS survey, based on the classification of National Bureau of Statistics of China.



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

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 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 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

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

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 40% 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), only 5% of them are observed not to be enrolled in school. This out-of-school rate rises to about 30% 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 enrollment could be due to the fact that this sample also received better education and are in a better economic condition in previous years. And they 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, 7 out of a total of 166 counties[9] 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 by the survey, so children who are not enrolled in the survey also take the test, and the scores are comparable every two years. The scores shown are z-scores adjusted for the

[9]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.

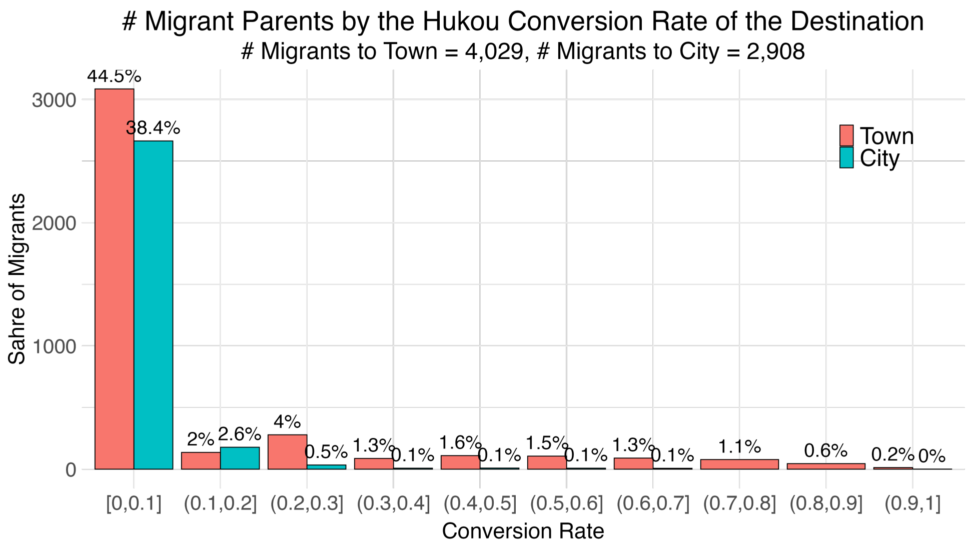


Figure 3: The Concentration of Migrants in Big and Restrictive Cities

Data Source: CFPS 2010-2020.

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 when they are actually separated from their city-migrant parents. From the education expenditures[10], 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), 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.

3.2.2 Migrant Parents

Figure 3 shows the distribution of the sample of migrant parents across town and city locations by the 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

[10] 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 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 urban destinations, 26.6% of them went to urban destinations, and the remainder moved across rural counties. For the sample of migrant parents of children aged 6 to 18, about the same proportion (29.2%) of them migrated to towns, but a smaller proportion (19.3%) 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 of nearly all demographic variables. 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 with the best economic background bring their children to the destination, and this is also contributed by the fact that their destination coincides with the first choice on the list.

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	17,632	1.91 (0.01)	39.5 (0)	51.8% (0.4%)	15.9 (0.2)	8.3% (0.2%)	37.5 (0)	39.6% (0.4%)	8.8 (0.1)	7.4% (0.2%)
Rural	Town (O)	3,621	1.73 (0.01)	41.4 (0.1)	56.5% (0.8%)	21.1 (0.6)	8.6% (0.5%)	39.8 (0.1)	46.6% (0.8%)	11 (0.2)	9.0% (0.5%)
Rural	City (O)	1,632	1.61 (0.02)	42.2 (0.2)	62.8% (1.2%)	24.5 (0.8)	13.7% (0.9%)	40.6 (0.1)	48.4% (1.2%)	14.1 (0.4)	11.8% (0.8%)
Town	Rural	3,576	1.79 (0.01)	38.9 (0.1)	65.9% (0.8%)	30.3 (0.7)	13.0% (0.6%)	36.8 (0.1)	54.4% (0.8%)	18.3 (0.6)	11.5% (0.5%)
Town	Town (O)	1,804	1.67 (0.02)	40.3 (0.2)	59.3% (1.2%)	20 (0.7)	13.0% (0.8%)	38.3 (0.1)	54.5% (1.2%)	12.9 (0.4)	12.3% (0.8%)
Town	City (O)	343	1.41 (0.03)	41.6 (0.3)	72.0% (2.4%)	37 (2.5)	12.5% (1.8%)	39.5 (0.3)	69.4% (2.5%)	24.2 (1.7)	12.9% (1.8%)
Town	Town (W)	1,194	1.67 (0.02)	39.3 (0.2)	64.0% (1.4%)	30.1 (1.1)	15.0% (1.0%)	37.3 (0.2)	55.3% (1.4%)	17.1 (0.7)	14.5% (1.0%)
Town	City (W)	652	1.55 (0.03)	40.7 (0.3)	74.2% (1.7%)	46.7 (2.7)	17.9% (1.5%)	39 (0.2)	67.2% (1.8%)	27.7 (1.8)	19.0% (1.5%)
City	Rural	1,307	1.5 (0.02)	40.7 (0.2)	81.6% (1.1%)	39.8 (1.9)	20.3% (1.1%)	38.8 (0.2)	73.1% (1.2%)	26.4 (1.1)	19.0% (1.1%)
City	Town (O)	314	1.61 (0.03)	40.4 (0.3)	77.7% (2.4%)	36.6 (3.2)	17.2% (2.1%)	38.3 (0.3)	74.8% (2.5%)	23.5 (2.2)	16.1% (2.1%)
City	City (O)	556	1.39 (0.02)	41 (0.2)	74.8% (1.8%)	38.8 (3)	17.4% (1.6%)	39.1 (0.2)	72.3% (1.9%)	24.6 (2.3)	16.2% (1.6%)
City	Town (W)	306	1.45 (0.04)	40 (0.3)	83.7% (2.1%)	47.9 (3.3)	22.5% (2.4%)	38.4 (0.3)	79.1% (2.3%)	27.3 (1.7)	26.2% (2.5%)
City	City (W)	807	1.43 (0.02)	39.7 (0.2)	81.4% (1.4%)	48.8 (2.3)	24.4% (1.5%)	37.8 (0.2)	79.2% (1.4%)	31.8 (1.5)	26.8% (1.6%)

[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 red, the lowest in green.

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[11] 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 (12-15).

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.

[11]Lagged test scores are from the period $t-2$ because CFPS standardized tests are comparable every two waves.

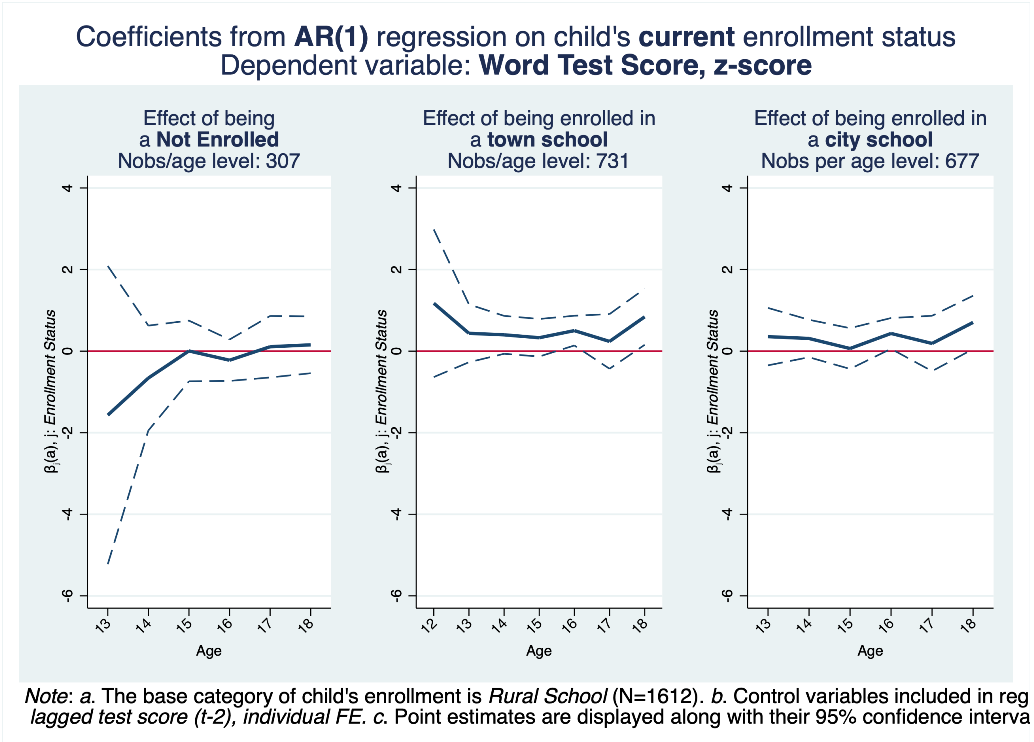


Figure 4: Child's Word Test Score Regression Coefficients

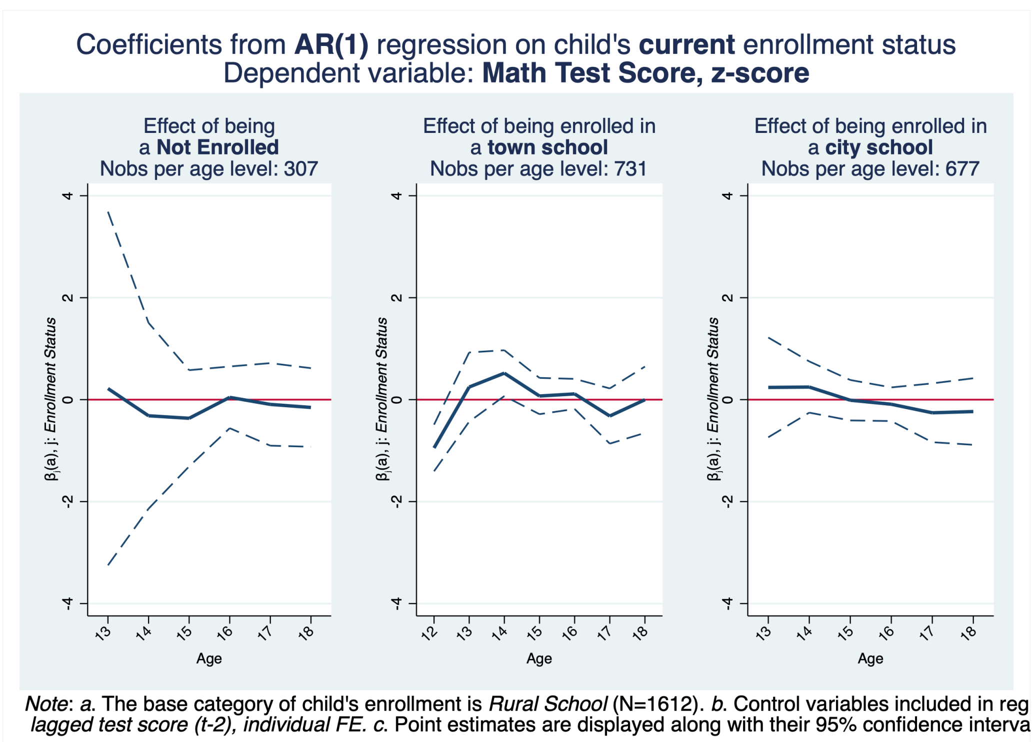


Figure 5: Child's Math Test Score Regression Coefficients

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 decision, the active decision maker is assumed to be the parent with migration opportunities. Figure 6 shows the tree structure of the model.

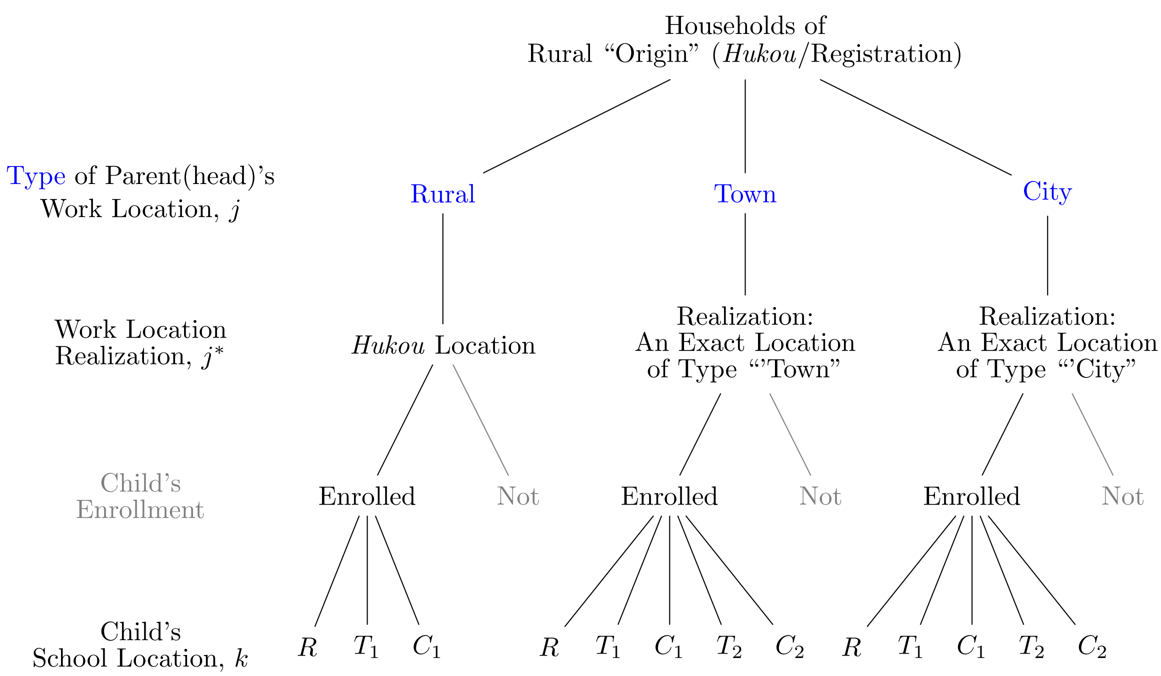


Figure 6: Tree Structure

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, 75.7% of the out-of-school rural-*Hukou* children stay in rural areas, 13.9% of them go to towns, and 5.3% 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 is decided, an exact location 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

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

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

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

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 linkages 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, 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, so 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

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

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

$$U^{(2)}_{j^*k} = \alpha_j \cdot z_{j^*k} + \mu_{jk} \cdot x^{(2)} + \varepsilon^{(2)}_{j^*k}$$

where $x^{(2)}$ includes the child's demographic variables and z_{j^*k} includes the benefits and costs of the child's education, which are assumed to affect the child's school location and the parent's work location only by affecting the child.

5 Estimation

In the nested structure, the model is estimated backwards in two stages (limited information maximum likelihood 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, 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 ρ_j from the next step to get the estimates for α and μ.

5.1.1 Costs of Education and Child's Academic Performance

The alternative-specific regressor vector z included in the school choice stage is the expected value for each alternative. The costs and benefits of education are included in z. Educational expenditures and the child's academic performance are included to capture these two aspects.

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

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

Expenditures are assumed to vary as the child grows and enters a new stage of education, and this age effect is allowed to differ by type (rural, town, or city) of school location (denoted by $j(k)$), and this effect is treated as non-linear as age is included as a set of dummies and then interacted with $j(k)$. And the regression also includes school location fixed effects and time fixed effects.

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

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

The z-score is used as the dependent variable, and the prediction is done separately for the word test and the math test. The z-score is already a standardized score adjusted for the child's age and gender, but it could still have an age trend across locations and time. And trying the prediction on many specifications confirms the age effect, and also suggests that gender has little 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 with log likelihood given by

$$\ln L_1 = \sum_i \sum_j d_{ij} \ln p_{ij}$$

where the choice probability is

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

using 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 for sure. 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), at most 6 possible destinations of each type (town or city) were observed in the data at baseline, and nearly all origins were observed to have at least three destinations associated with them in terms of historical migration stock. Thus, for each individual, there are three potential town locations and three potential city locations in each pool of j. And 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, including 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 education level of the migrant applicant across location types, reflecting the spatial variation in *Hukou* policies, as well as the variation in the success rate of the conversion process across education levels.

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 has 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 is that it has variation only for city locations, not for town locations as I have defined them, which are not as restrictive as cities.

The *Hukou* conversion rate 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), ^{p} denotes the parent, a is age, and e is educational attainment. Place and time fixed effects are also included. The return to education is allowed to differ by location type, capturing the fact that returns to education would be higher in more developed urban locations.

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 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. And this suggests that households are more sensitive to education expenditure 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 the regressors 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 worse schools. Coefficients for the individual-specific regressors from the lower nest can be found in tables A3, A4, and A5.

Table 4 shows the results from the upper nest. The negative coefficients on the conversion rate suggest 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 parents of middle school-aged children and is larger when the household comes from an origin without a secondary school. For the individual-specific regressors whose coefficients vary across alternatives, the estimates can be interpreted as the effect on the choice of the alternative relative to the base category. Having more children reduces the probability

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)	0.001				
	(0.020)				
No. Primary Schools (Work = T)	-0.008				
	(0.029)				
No. Primary Schools (Work = C)	-0.775***				
	(0.108)				
No. Secondary Schools (Work = R)		0.065	-0.025	-0.035	-0.014
		(0.071)	(0.052)	(0.203)	(0.160)
No. Secondary Schools (Work = T)		-0.094	-0.130	-0.728	-0.525
		(0.095)	(0.079)	(0.488)	(0.291)
No. Secondary Schools (Work = C)		-0.429	-0.487	-1.091	-1.959*
		(0.286)	(0.385)	(0.667)	(0.901)
Word Score, z (Work = R)		-0.530***	-0.161	-0.529*	-0.501**
		(0.110)	(0.093)	(0.206)	(0.180)
Word Score, z (Work = T)		0.099	0.257*	0.150	0.296
		(0.122)	(0.117)	(0.225)	(0.202)
Word Score, z (Work = C)		0.081	0.301*	0.126	0.023
		(0.143)	(0.119)	(0.257)	(0.222)
Edu. Expenses (Work = R)	-0.067*	-0.074	-0.077	-0.022	0.243**
	(0.032)	(0.039)	(0.054)	(0.114)	(0.091)
Edu. Expenses (Work = T)	-0.006	-0.059	-0.098	-0.038	0.165
	(0.033)	(0.041)	(0.056)	(0.115)	(0.092)
Edu. Expenses (Work = C)	0.007	0.002	-0.063	0.042	0.200*
	(0.036)	(0.045)	(0.059)	(0.117)	(0.096)
N	225,745	109,174	103,753	45,591	43,420
Log-likelihood	-26916.2	-13669.1	-15268.1	-5779.4	-6231.9

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 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)	0.457***	0.690***	0.558***	0.731***	0.918***
	(0.112)	(0.069)	(0.092)	(0.128)	(0.127)
Inclusive Value (Work=T)	0.095	0.554***	0.567***	0.639*	0.864***
	(0.219)	(0.163)	(0.104)	(0.292)	(0.129)
Inclusive Value (Work=C)	0.738***	0.332	0.663***	0.731	0.880***
	(0.115)	(0.266)	(0.129)	(0.390)	(0.143)
Income	0.073	0.120	-0.047	0.489***	0.249*
	(0.054)	(0.068)	(0.069)	(0.104)	(0.101)
Housing Price	-0.019**	-0.046***	-0.005	-0.069***	-0.008
	(0.007)	(0.011)	(0.010)	(0.021)	(0.017)
Conversion Rate	-0.782***	-1.010***	-0.936***	-1.132***	-1.136***
	(0.090)	(0.115)	(0.113)	(0.193)	(0.188)
Work Location: Town					
Age (Parent)	0.017	-0.008	-0.005	-0.201*	-0.126
	(0.041)	(0.062)	(0.067)	(0.099)	(0.114)
Age-sq. (Parent)	-0.000	0.000	0.000	0.002*	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Completes 9-yr Edu. (Parent)	0.481***	0.304***	0.025	0.177	-0.040
	(0.059)	(0.074)	(0.073)	(0.116)	(0.115)
No. Children (Parent)	-0.153***	-0.080	-0.132*	-0.107	-0.142
	(0.036)	(0.046)	(0.052)	(0.077)	(0.086)
Constant	-2.261**	-1.602	-1.081	2.853	2.242
	(0.785)	(1.427)	(1.641)	(2.258)	(2.716)
Work Location: City					
Age (Parent)	0.548***	0.474**	0.446**	0.381	0.270
	(0.094)	(0.154)	(0.169)	(0.262)	(0.225)
Age-sq. (Parent)	-0.006***	-0.005**	-0.004*	-0.004	-0.003
	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)
Completes 9-yr Edu. (Parent)	1.122***	1.167***	0.826***	1.133***	1.126***
	(0.101)	(0.122)	(0.119)	(0.188)	(0.195)
No. Children (Parent)	-0.716***	-0.707***	-0.381***	-0.781***	-0.494***
	(0.070)	(0.085)	(0.090)	(0.136)	(0.143)
Constant	-12.366***	-12.736***	-12.525**	-10.133	-7.917
	(1.856)	(3.392)	(4.023)	(5.817)	(5.283)
N	43,335	21,594	20,658	9,627	9,156
Log-likelihood	-9981.1	-4780.3	-4866.1	-2020.8	-1975.5

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.

that parents will work outside rural areas, and even more so that they will work in cities.

6 Counterfactual Exercises

This section presents the results of two counterfactual exercises that explore policies that could increase the welfare of rural households, or at least those that could 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 households with children.

The effects of two types of counterfactuals are evaluated: the education subsidy and the house price decline[12]. Panel B 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 place of work and the child's place 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 at primary-school age, and most likely to be separated from its city-migrant parent at middle-school age.

6.1 Education Subsidy

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. Two counterfactual exercises are then conducted to explore the effects of education subsidies at origin and destination.

Panel B of Table 5 shows the predicted choice probabilities from the model under a counterfactual economy where education spending is reduced by 20% if the child is enrolled at origin. For children aged 6 to 12 in primary school, there is little effect on parents' choice of location, consistent with the fact that education costs are not a major concern for the family budget if the child attends a primary school in rural areas. And this result is consistent with the results from Table 6 and Table 7. And for this age

[12]The effects of an agricultural income shock are also evaluated, although they are not significant

Table 5: Predicted Choice Probabilities of Parental Migration

Work Location	Age Group		
	Age [6,12)	Age [12,15)	Age [15,18]
	A. Baseline		
Rural	0.233	0.323	0.524
Town	0.721	0.257	0.332
City	0.046	0.421	0.144
	B. Edu. Expenses Subsidy in Rural Areas (20%)		
Rural	0.232 (-0.1pp.)	0.272 (-15.7pp.)	0.566 (+7.9pp.)
Town	0.722 (+0.0pp.)	0.168 (-34.4pp.)	0.308 (-7.2pp.)
City	0.046 (+0.0pp.)	0.56 (+33.1pp.)	0.126 (-12.1pp.)
	C. Edu. Expenses Subsidy at Destination (10%)		
Rural	0.146 (-37.4pp.)	0.329 (+1.9pp.)	0.519 (-1.0pp.)
Town	0.826 (+14.5pp.)	0.269 (+4.7pp.)	0.333 (+0.3pp.)
City	0.028 (-38.0pp.)	0.402 (-4.4pp.)	0.148 (+3.0pp.)
	D. House Price Drop (Town: 15%, City: 10%)		
Rural	0.235 (+1.1pp.)	0.323 (+0.2pp.)	0.525 (+0.1pp.)
Town	0.719 (-0.3pp.)	0.253 (-1.6pp.)	0.331 (-0.2pp.)
City	0.046 (-0.1pp.)	0.424 (+0.8pp.)	0.144 (+0.2pp.)

Table 6: Predicted Probabilities of Parent-Child Separation

Work Location	Age Group		
	Age [6,12)	Age [12,15)	Age [15,18]
	A. Baseline		
Town	0.426	0.148	0.177
City	0.034	0.331	0.112
	B. Edu. Expenses Subsidy in Rural Areas (20%)		
Town	0.426 (+0.1pp.)	0.097 (-34.2pp.)	0.163 (-8.0pp.)
City	0.034 (+0.0pp.)	0.442 (+33.6pp.)	0.098 (-12.2pp.)
	C. Edu. Expenses Subsidy at Destination (10%)		
Town	0.506 (+18.8pp.)	0.155 (+4.7pp.)	0.178 (+0.4pp.)
City	0.021 (-38.0pp.)	0.316 (-4.4pp.)	0.115 (+3.1pp.)
	D. House Price Drop (Town: 15%, City: 10%)		
Town	0.424 (-0.4pp.)	0.145 (-1.5pp.)	0.176 (-0.2pp.)
City	0.034 (-0.1pp.)	0.333 (+0.8pp.)	0.112 (+0.2pp.)

Table 7: Predicted Vocabulary Test Scores, Z-Score

School Location	Age Group: Age [6,12)	Age [12,15)	Age [15,18]
	A. Baseline		
Rural	0.026	0.03	0.024
Town	0.019	0.018	0.016
City	0.019	0.017	0.015
	B. Edu. Expenses Subsidy in Rural Areas (20%)		
Rural	0.026 (-0.1%)	0.027 (-8.4%)	0.026 (+9.0%)
Town	0.019 (-0.2%)	0.018 (+2.6%)	0.015 (-3.6%)
City	0.019 (+0.4%)	0.019 (+9.3%)	0.014 (-5.5%)
	C. Edu. Expenses Subsidy at Destination (10%)		
Rural	0.019 (-25.3%)	0.03 (+1.0%)	0.023 (-0.6%)
Town	0.019 (-0.4%)	0.018 (-0.2%)	0.016 (+0.3%)
City	0.024 (+25.9%)	0.017 (-1.2%)	0.015 (+0.3%)
	D. House Price Drop (Town: 15%, City: 10%)		
Rural	0.026 (+0.6%)	0.03 (+0.0%)	0.024 (+0.0%)
Town	0.019 (0.0%)	0.018 (-0.1%)	0.016 (0.0%)
City	0.019 (-0.5%)	0.017 (+0.1%)	0.015 (0.0%)

group, the effects on town and city are are not digtinguished from each other could be due to the reason that city and town schools don't produce differently on child 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. For children aged 12 to 15 in middle school, with a subsidy in rural areas will cause their parents to migrate to cities more, and accompanied with a family separation. Although not all children of these new migrants are brought to the destination, this increase in urban migration still brings many children to the destination, and we see an increase in the academic performance of rural children attending school in urban ares, which could come from the sorting in migration and migration with children. This subsidy at origin leads to a substitution effect within the budget constraint of migrant parents, incentivizing them to reallocate resources from children's education to migration. For children between the ages of 15 and 18, who are generally out of compulsory schooling and have to pay for more expensive schooling, the subsidy increases their school performance, reduces parental migration, and decreases family separation. The resource reallocation explanation still holds, and since children in rural areas can now receive more and better educational inputs, they will drop out less and provide less agricultural labor than they would have if they were not in school (Antman, 2011). This could be a reason to keep their parents in rural areas, and parents of children in this age group also have less incentive to migrate.

Panel C of Table 5, Table 6, and Table 7 examines the effect of a 10% reduction in the cost of education at the parent's destination. A 10% is chosen, rather than 20% as for the origin subsidy, because schooling at the destination is clearly more expensive than at the origin. Unlike the subsidy at origin, the effects on primary school-aged children are not the most affected, for a substantial effect. Town destinations now become less expensive and attract more migrants, both new migrants from rural areas and those who have moved from the cities. And this migration pattern further reduces parent-child separation for city migrants and increases it for town migrants. And parents of children aged 15 to 18 are migrating more, and many are bringing their children to the destination, which leads to an increase in the test scores of those children.

6.2 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.

Panel E of Table 5 and Panel F of Table A7 report the predicted choice probabilities from the model under this counterfactual economy. And they both 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.

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 show that the impact of parental migration on children's education differs by children's educational level. Policies on the migration destination side affect households with primary school-aged children the most, while parents of middle school-aged children are the group with the highest motivation to migrate for better educational opportunities for their children. And high school-aged children are the group most sensitive to budget constraints, with parents having the lowest substitution between education and migration resources within the household budget. The results also suggest 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. And because of the difficulty of settlement caused by the restrictions, rural children are very little affected by the volatility of the housing market.

This paper extends the scope of modeling labor migration to the household decision, allowing for the exploration of more dimensions of child inputs and outcomes than a binary variable of leaving children behind as in existing research. And the rural-urban division of the model is also more comprehensive and realistic to account for the regional variations brought about by the rapid urbanization process. 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.

References

Adamopoulos, Tasso, Brandt, Loren, Chen, Chaoran, Restuccia, Diego, and Wei, Xiaoyun (2024). “Land Security and Mobility Frictions”. *The Quarterly Journal of Economics* 139.3, pp. 1941–1987.

Akbar, Prottoy, Couture, Victor, Duranton, Gilles, and Storeygard, Adam (2023). “Mobility and Congestion in Urban India”. *American Economic Review* 113.4, pp. 1083–1111.

Albert, Christoph and Monras, Joan (2022). “Immigration and Spatial Equilibrium: The Role of Expenditures in the Country of Origin”. *American Economic Review* 112.11, pp. 3763–3802.

Ambler, Kate, Aycinena, Diego, and Yang, Dean (2015). “Channeling Remittances to Education: A Field Experiment among Migrants from El Salvador”. *American Economic Journal: Applied Economics* 7.2, pp. 207–232.

Antman, Francisca M. (2011). “International Migration and Gender Discrimination among Children Left Behind”. *American Economic Review* 101.3, pp. 645–649.

— (2012). “Gender, Educational Attainment, and the Impact of Parental Migration on Children Left Behind”. *Journal of Population Economics* 25.4, pp. 1187–1214.

— (2013). “The Impact of Migration on Family Left Behind”. *International Handbook on the Economics of Migration*. Edward Elgar Publishing, pp. 293–308.

Bai, Yu, Zhang, Linxiu, Liu, Chengfang, Shi, Yaojiang, Mo, Di, and Rozelle, Scott (2018). “Effect of Parental Migration on the Academic Performance of Left Behind Children in North Western China”. *The Journal of Development Studies* 54.7, pp. 1154–1170.

Borjas, George J and Cassidy, Hugh (2019). “The Wage Penalty to Undocumented Immigration”. *Labour Economics* 61, p. 101757.

Brueckner, Jan K. and Lall, Somik V. (2015). “Cities in Developing Countries”. *Handbook of Regional and Urban Economics*. Vol. 5. Elsevier, pp. 1399–1455.

Bryan, Gharad and Morten, Melanie (2019). “The Aggregate Productivity Effects of Internal Migration: Evidence from Indonesia”. *Journal of Political Economy* 127.5, pp. 2229–2268.

Cai, Fang, Du, Yang, and Wang, Meiyan (2001). "Household Registration System and Labor Market Protection". *Economic Research Journal* 12.5, pp. 41–49.

Chan, Kam Wing (2018). "China's Hukou System at 60: Continuity and Reform". *Handbook on Urban Development in China*. Edward Elgar Publishing, pp. 59–79.

Chen, Shuai, Oliva, Paulina, and Zhang, Peng (2022). "The Effect of Air Pollution on Migration: Evidence from China". *Journal of Development Economics* 156.102833.

Constant, Amelie and Klaus F. Zimmermann, eds. (2013). *International Handbook on the Economics of Migration*. Cheltenham: Edward Elgar. 573 pp.

Francesconi, Marco and Heckman, James J. (2016). "Child Development and Parental Investment: Introduction". *The Economic Journal* 126.596, F1–F27.

Gao, Xuwen, Liang, Wenquan, Mobarak, Ahmed Mushfiq, and Song, Ran (2023). "Restrictions on Migration Create Gender Inequality: The Story of China's Left-Behind Children".

Garriga, Carlos, Hedlund, Aaron, Tang, Yang, and Wang, Ping (2023). "Rural-Urban Migration, Structural Transformation, and Housing Markets in China". *American Economic Journal: Macroeconomics* 15.2, pp. 413–440.

Imbert, Clement, Seror, Marlon, Zhang, Yifan, and Zylberberg, Yanos (2022). "Migrants and Firms: Evidence from China". *American Economic Review* 112.6, pp. 1885–1914.

Imbert, Clément, Monras, Joan, Seror, Marlon, and Zylberberg, Yanos (2024). "Floating Population: Migration With(Out) Family and the Spatial Distribution of Economic Activity".

Khanna, Gaurav, Liang, Wenquan, Mobarak, Ahmed Mushfiq, and Song, Ran (2021). "The Productivity Consequences of Pollution-Induced Migration in China".

Kinnan, Cynthia, Wang, Shing-Yi, and Wang, Yongxiang (2018). "Access to Migration for Rural Households". *American Economic Journal: Applied Economics* 10.4, pp. 79–119.

Lagakos, David, Mobarak, Ahmed Mushfiq, and Waugh, Michael E. (2023). "The Welfare Effects of Encouraging Rural–Urban Migration". *Econometrica* 91.3, pp. 803–837.

Liu, Yanan and Tang, Yugang (2021). "Epidemic Shocks and Housing Price Responses: Evidence from China's Urban Residential Communities". *Regional Science and Urban Economics* 89, p. 103695.

Marchetta, Francesca and Sim, Sokcheng (2021). "The Effect of Parental Migration on the Schooling of Children Left behind in Rural Cambodia". *World Development* 146, p. 105593.

Meng, Xin, Qian, Nancy, and Yared, Pierre (2015). "The Institutional Causes of China's Great Famine, 1959-1961". *The Review of Economic Studies* 82 (4 (293)), pp. 1568–1611. JSTOR: 43869477.

Peking University, Institute of Social Science Survey (2015). *China Family Panel Studies (CFPS)*. Version V42.

Rogoff, Kenneth and Yang, Yuanchen (2021). "Has China's Housing Production Peaked?" *China & World Economy* 29.1, pp. 1–31.

Selod, Harris and Shilpi, Forhad (2021). "Rural-Urban Migration in Developing Countries: Lessons from the Literature". *Regional Science and Urban Economics*.

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

Tang, Zequn and Wang, Ning (2021). "School Disruption of Children in China: The Influence of Parents' Rural–Urban Migration". *Children and Youth Services Review* 129, p. 106167.

Tombe, Trevor and Zhu, Xiaodong (2019). "Trade, Migration, and Productivity: A Quantitative Analysis of China". *American Economic Review* 109.5, pp. 1843–1872.

United Nations, Department of Economics and Social Affairs (2015). "World Population Policies 2015". New York, NY: United Nations.

Wu, Wenbin and You, Wei (2024). *Should Governments Promote or Restrain Urbanization? A Quantitative Analysis of the Internal Migration Restrictions in China*. (Visited on 11/03/2024). Pre-published.

Yang, Guanyi and Bansak, Cynthia (2020). "Does Wealth Matter? An Assessment of China's Rural-Urban Migration on the Education of Left-behind Children". *China Economic Review* 59, p. 101365.

Zhang, Jipeng, Huang, Jin, Wang, Junhui, and Guo, Liang (2020). "Return Migration and Hukou Registration Constraints in Chinese Cities". *China Economic Review* 63.101498.

Zhang, Jipeng, Wang, Ru, and Lu, Chong (2019). "A Quantitative Analysis of *Hukou* Reform in Chinese Cities: 2000-2016". *Growth and Change* 50.1, pp. 201–221.

Zhong, Ling (2024). "Internal Migration and Extended Families in China".

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

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

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, which total 13. Marginal effects are not calculated for these regressors because they are

Table A1: CFPS Sample sizes

	Number of sampled individuals aged			
Wave	[0,5]	[6,14]	[15,18]	[19,50]
2010	3,614	4,986	1,980	19,151
2012	3,551	4,642	2,096	21,465
2014	3,597	4,572	1,952	21,332
2016	2,989	4,566	2,293	20,413
2018	2,240	4,821	1,603	18,278
2020	859	3,982	1,251	13,930
2022	55	3,542	1,244	12,572

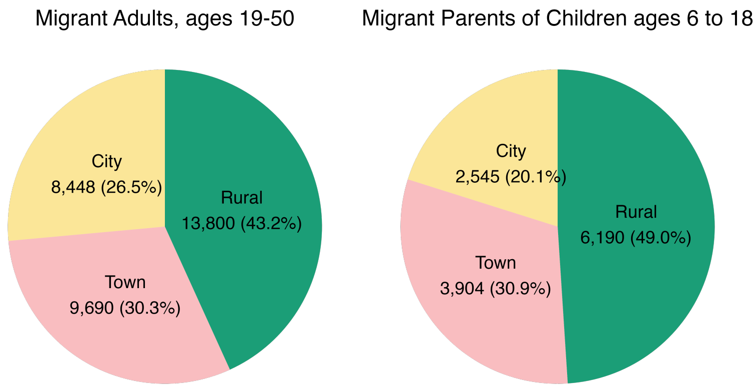
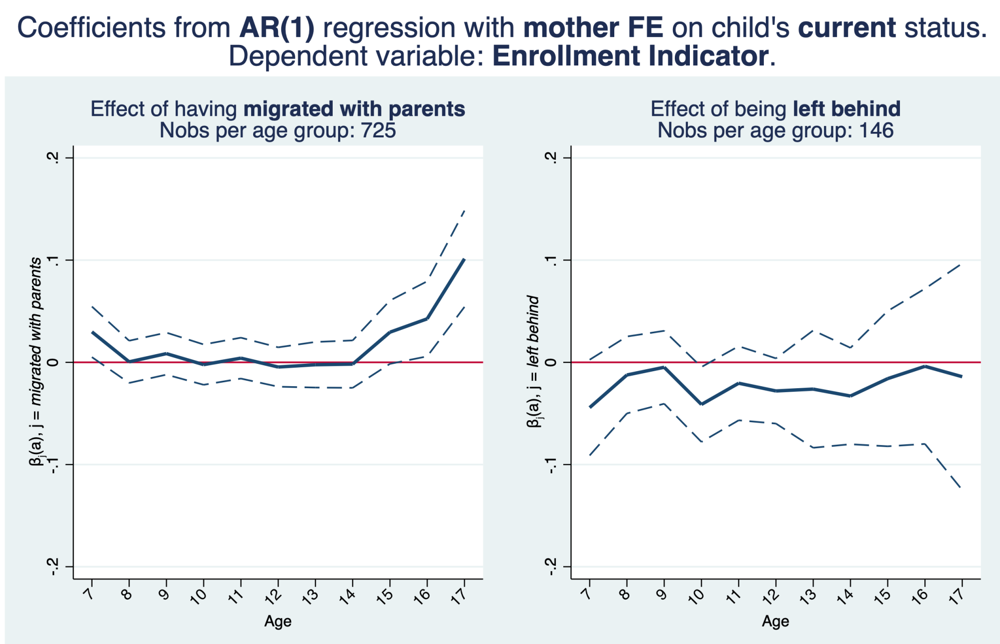


Figure A1: Migrants and Migrant Parents by Type of Destination



Note: *a.* The base category of child's status is children of *non-migrant parents*. *b.* Control variables included in the regressions: **lagged outcome**, child's gender, living province dummies, parents education, occupation, and income. *c.* Point estimates are displayed along with their 95% confidence intervals.

Figure A2: Migration Outcome Gap on Enrollment Rate: Estimates for $\beta_j(a_{it})$ from the dynamic panel (Appendix A.1)

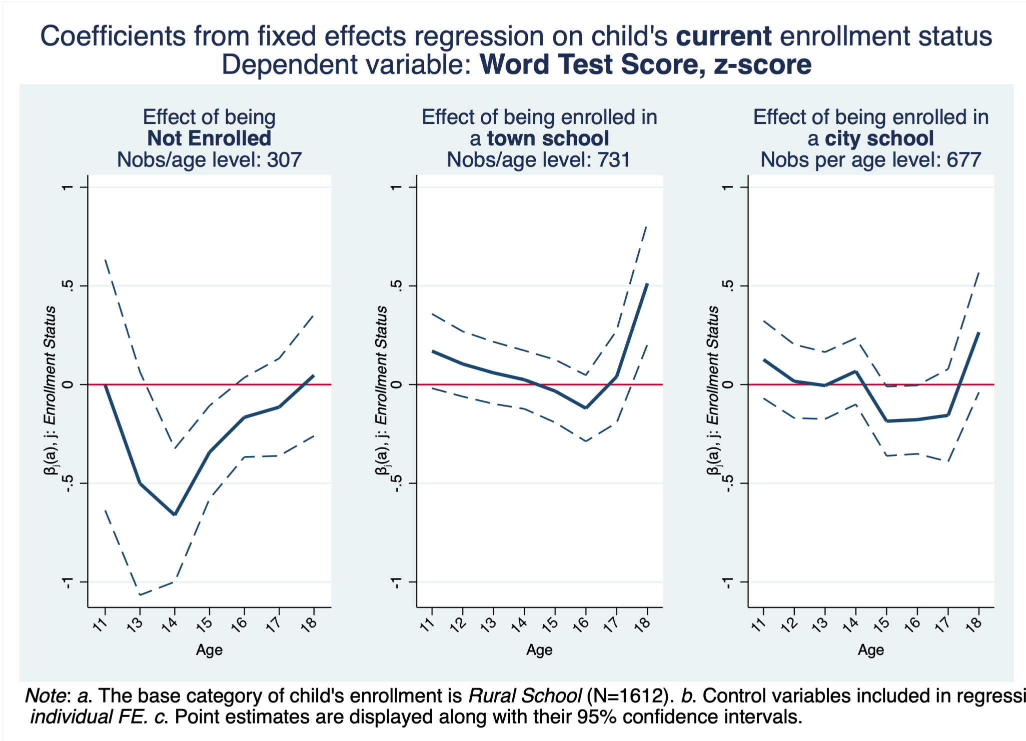


Figure A3: Child's Word Test Score Regression Coefficients

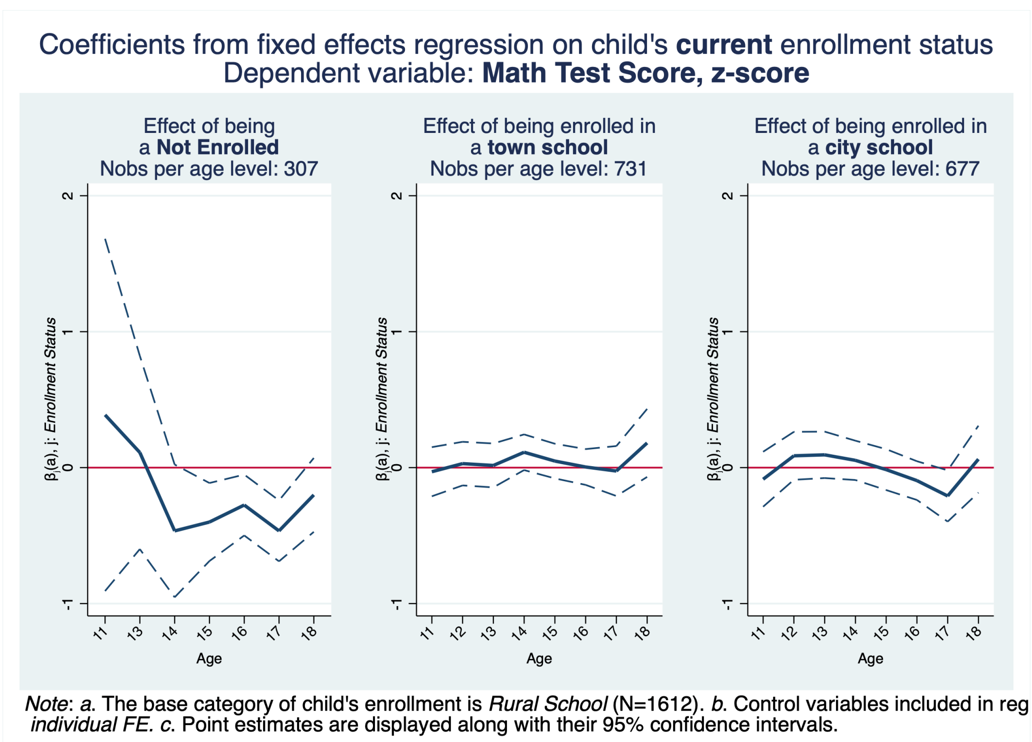


Figure A4: Child's Math Test Score Regression Coefficients reported for each of the thirteen alternatives, so there are 13 $times 13 = 169$ effects for each regressor.

Table A2: Regression for Predicting Alternative-Specific Variables

	Dependent Variable			
	Income	Edu. Expense	Word Score	Math Score
Constant	5.730***	8.788***	0.626***	0.370***
	(0.198)	(0.247)	(0.101)	(0.103)
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	42,652	19,578	18,847
R^2	0.224	0.370	0.259	0.240

*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)	0.164	1.040	1.323	1.644	1.870
	(0.205)	(2.060)	(0.987)	(2.752)	(1.498)
Age-sq. (Child)	-0.008	-0.035	-0.033	-0.057	-0.048
	(0.012)	(0.079)	(0.030)	(0.106)	(0.046)
Male (Child)	0.097	0.100	-0.015	0.216*	-0.014
	(0.078)	(0.080)	(0.067)	(0.107)	(0.096)
Constant	-1.884*	-8.689	-12.920	-12.639	-17.813
	(0.856)	(13.364)	(8.090)	(17.854)	(12.229)
Work=R, Edu=C1					
Age (Child)	-0.196	-2.631	2.394*	1.705	5.261**
	(0.333)	(3.340)	(1.204)	(4.870)	(1.834)
Age-sq. (Child)	0.012	0.107	-0.063	-0.059	-0.143**
	(0.020)	(0.128)	(0.036)	(0.187)	(0.056)
Male (Child)	0.094	0.088	-0.008	0.220	0.098
	(0.118)	(0.125)	(0.081)	(0.185)	(0.121)
Constant	-0.737	14.243	-22.937*	-14.236	-48.392**
	(1.375)	(21.673)	(9.912)	(31.601)	(15.082)
N	225,745	109,174	103,753	45,591	43,420
Log-likelihood	-26916.2	-13669.1	-15268.1	-5779.4	-6231.9

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)	-0.007	-1.824	-1.207	-4.034	-2.521
	(0.144)	(2.149)	(1.737)	(3.758)	(3.600)
Age-sq. (Child)	0.000	0.068	0.035	0.153	0.072
	(0.008)	(0.083)	(0.053)	(0.145)	(0.111)
Male (Child)	0.001	0.045	0.117	0.104	0.457*
	(0.058)	(0.082)	(0.107)	(0.140)	(0.204)
Constant	-0.128	11.062	9.116	25.099	19.642
	(0.595)	(13.903)	(14.112)	(24.298)	(29.182)
Work=T, Edu=T1					
Age (Child)	-0.036	-0.233	1.686	0.224	1.912
	(0.238)	(2.865)	(1.479)	(4.764)	(2.640)
Age-sq. (Child)	0.002	0.009	-0.047	-0.004	-0.052
	(0.014)	(0.110)	(0.045)	(0.183)	(0.080)
Male (Child)	-0.007	0.080	-0.000	0.161	-0.222
	(0.087)	(0.114)	(0.107)	(0.187)	(0.182)
Constant	-0.112	0.014	-15.773	-3.916	-18.769
	(0.983)	(18.551)	(12.111)	(30.880)	(21.590)
Work=T, Edu=C1					
Age (Child)	-0.022	-0.769	0.414	-4.387	-1.702
	(0.553)	(6.283)	(2.726)	(12.745)	(4.749)
Age-sq. (Child)	0.002	0.032	-0.005	0.171	0.061
	(0.032)	(0.241)	(0.082)	(0.490)	(0.143)
Male (Child)	-0.007	-0.083	0.039	0.247	0.138
	(0.190)	(0.233)	(0.211)	(0.462)	(0.368)
Constant	-0.388	2.212	-7.219	24.940	8.597
	(2.325)	(40.752)	(22.512)	(82.591)	(39.186)
Work=T, Edu=T2					
Age (Child)	-0.015	2.225	2.000	5.876	2.787
	(0.277)	(3.401)	(1.844)	(4.148)	(2.397)
Age-sq. (Child)	0.001	-0.085	-0.055	-0.223	-0.077
	(0.016)	(0.131)	(0.056)	(0.160)	(0.073)
Male (Child)	0.010	0.186	0.010	0.327	-0.049
	(0.099)	(0.138)	(0.125)	(0.175)	(0.164)
Constant	-0.211	-16.266	-19.036	-40.347	-26.106
	(1.140)	(22.019)	(15.158)	(26.872)	(19.668)
Work=T, Edu=C2					
Age (Child)	-0.051	3.104	1.829	5.490	2.554
	(0.389)	(4.917)	(2.098)	(7.185)	(3.341)
Age-sq. (Child)	0.003	-0.118	-0.046	-0.209	-0.060
	(0.023)	(0.189)	(0.063)	(0.276)	(0.101)
Male (Child)	0.024	0.024	-0.048	0.169	0.014
	(0.142)	(0.188)	(0.140)	(0.286)	(0.221)
Constant	-0.159	-22.484	-18.881	-38.343	-27.731
	(1.600)	(31.874)	(17.302)	(46.575)	(27.543)
N	225,745	109,174	103,753	45,591	43,420
Log-likelihood	-26916.2	-13669.1	-15268.1	-5779.4	-6231.9

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)	-0.108	-0.607	0.131	-4.256	-5.441
	(0.242)	(3.288)	(1.799)	(7.310)	(3.866)
Age-sq. (Child)	0.007	0.024	0.002	0.170	0.174
	(0.014)	(0.126)	(0.055)	(0.281)	(0.117)
Male (Child)	0.010	0.058	0.075	0.342	0.152
	(0.104)	(0.131)	(0.142)	(0.269)	(0.341)
Constant	-1.583	2.725	-4.414	23.439	39.605
	(1.024)	(21.304)	(14.737)	(47.369)	(31.701)
Work=C, Edu=T1					
Age (Child)	0.263	1.815	4.268	9.882	11.396
	(0.530)	(6.015)	(3.852)	(9.270)	(5.955)
Age-sq. (Child)	-0.010	-0.069	-0.124	-0.370	-0.331
	(0.030)	(0.231)	(0.117)	(0.355)	(0.180)
Male (Child)	0.297	0.081	-0.146	0.019	-0.563
	(0.193)	(0.232)	(0.254)	(0.350)	(0.394)
Constant	-5.135*	-13.502	-39.025	-69.194	-100.305*
	(2.232)	(38.950)	(31.627)	(60.357)	(49.157)
Work=C, Edu=C1					
Age (Child)	-0.138	2.225	3.382	2.133	1.712
	(0.407)	(4.548)	(2.544)	(7.419)	(4.296)
Age-sq. (Child)	0.012	-0.086	-0.095	-0.082	-0.039
	(0.023)	(0.175)	(0.077)	(0.285)	(0.130)
Male (Child)	-0.121	-0.005	-0.022	-0.211	0.206
	(0.159)	(0.181)	(0.185)	(0.288)	(0.305)
Constant	-2.920	-15.740	-31.997	-16.661	-20.104
	(1.719)	(29.467)	(20.900)	(48.064)	(35.422)
Work=C, Edu=T2					
Age (Child)	0.311	2.800	1.861	9.554	-1.671
	(0.501)	(6.776)	(3.853)	(9.008)	(4.823)
Age-sq. (Child)	-0.018	-0.110	-0.052	-0.377	0.055
	(0.029)	(0.261)	(0.117)	(0.349)	(0.146)
Male (Child)	0.250	0.074	-0.117	0.518	-0.080
	(0.179)	(0.270)	(0.266)	(0.364)	(0.325)
Constant	-4.840*	-19.476	-19.260	-63.845	9.881
	(2.085)	(43.782)	(31.702)	(58.011)	(39.621)
Work=C, Edu=C2					
Age (Child)	-0.594*	1.047	3.398	2.068	5.599
	(0.302)	(4.263)	(2.388)	(6.782)	(3.595)
Age-sq. (Child)	0.031	-0.042	-0.094	-0.086	-0.158
	(0.018)	(0.164)	(0.072)	(0.262)	(0.109)
Male (Child)	0.132	0.080	0.071	0.281	0.151
	(0.120)	(0.170)	(0.178)	(0.260)	(0.261)
Constant	0.276	-7.773	-32.356	-15.246	-51.542
	(1.236)	(27.550)	(19.664)	(43.710)	(29.646)
N	225,745	109,174	103,753	45,591	43,420
Log-likelihood	-26916.2	-13669.1	-15268.1	-5779.4	-6231.9

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		
	R	0.582	0.547	0.368
Rural	T1	0.063	0.108	0.204
	C1	0.022	0.037	0.117
	R	0.128	0.104	0.06
	T1	0.049	0.051	0.066
Town	C1	0.008	0.01	0.015
	T2	0.034	0.031	0.042
	C2	0.015	0.015	0.033
	R	0.04	0.039	0.037
	T1	0.009	0.01	0.009
City	C1	0.014	0.018	0.02
	T2	0.01	0.008	0.008
	C2	0.026	0.022	0.021
		B. Baseline Model Prediction		
	R	0.147	0.218	0.235
Rural	T1	0.053	0.071	0.168
	C1	0.033	0.034	0.121
	R	0.165	0.092	0.082
	T1	0.15	0.062	0.088
Town	C1	0.127	0.025	0.038
	T2	0.145	0.047	0.068
	C2	0.135	0.031	0.058
	R	0.016	0.109	0.046
	T1	0.005	0.071	0.018
City	C1	0.007	0.086	0.031
	T2	0.006	0.065	0.017
	C2	0.012	0.09	0.032

Table A7: Predicted Choice Probabilities: Nested Choices

Work Location	School Location	Age Group: Age [6,12)	Age [12,15)	Age [15,18]
C. Edu. Expenses Subsidy in Rural Areas (20%)				
Rural	R	0.146 (-0.4pp.)	0.182 (-16.9pp.)	0.254 (+8.1pp.)
	T1	0.053 (+0.2pp.)	0.061 (-13.8pp.)	0.181 (+7.8pp.)
	C1	0.033 (+0.5pp.)	0.03 (-12.0pp.)	0.13 (+7.7pp.)
Town	R	0.164 (-0.5pp.)	0.064 (-30.6pp.)	0.076 (-6.5pp.)
	T1	0.15 (-0.1pp.)	0.041 (-33.7pp.)	0.083 (-5.6pp.)
	C1	0.127 (+0.6pp.)	0.015 (-41.1pp.)	0.033 (-11.0pp.)
	T2	0.145 (+0.0pp.)	0.03 (-36.0pp.)	0.063 (-7.4pp.)
	C2	0.135 (+0.3pp.)	0.019 (-39.4pp.)	0.053 (-8.1pp.)
City	R	0.016 (+0.0pp.)	0.136 (+24.6pp.)	0.041 (-11.3pp.)
	T1	0.005 (0.0pp.)	0.1 (+39.5pp.)	0.016 (-13.7pp.)
	C1	0.007 (0.0pp.)	0.114 (+32.9pp.)	0.027 (-11.8pp.)
	T2	0.006 (0.0pp.)	0.092 (+43.1pp.)	0.015 (-14.0pp.)
	C2	0.012 (0.0pp.)	0.118 (+31.1pp.)	0.028 (-11.8pp.)
D. Edu. Expenses Subsidy at Destination (10%)				
Rural	R	0.091 (-38.4pp.)	0.222 (+1.9pp.)	0.233 (-0.9pp.)
	T1	0.034 (-36.1pp.)	0.072 (+2.0pp.)	0.166 (-1.1pp.)
	C1	0.021 (-35.0pp.)	0.034 (+2.1pp.)	0.12 (-1.2pp.)
Town	R	0.144 (-12.8pp.)	0.095 (+3.9pp.)	0.082 (+0.2pp.)
	T1	0.157 (+4.6pp.)	0.065 (+4.5pp.)	0.088 (+0.1pp.)
	C1	0.187 (+47.4pp.)	0.026 (+6.2pp.)	0.038 (+0.7pp.)
	T2	0.163 (+12.1pp.)	0.049 (+5.0pp.)	0.068 (+0.3pp.)
	C2	0.176 (+30.5pp.)	0.033 (+5.8pp.)	0.058 (+0.4pp.)
City	R	0.01 (-37.7pp.)	0.105 (-3.4pp.)	0.047 (+2.6pp.)
	T1	0.003 (-38.4pp.)	0.068 (-5.1pp.)	0.019 (+3.8pp.)
	C1	0.005 (-38.2pp.)	0.082 (-4.4pp.)	0.032 (+3.0pp.)
	T2	0.004 (-38.4pp.)	0.061 (-5.5pp.)	0.018 (+3.9pp.)
	C2	0.007 (-37.8pp.)	0.086 (-4.1pp.)	0.033 (+2.9pp.)
E. House Price Drop (Town: 15%, City: 10%)				
Rural	R	0.148 (+1.0pp.)	0.219 (+0.2pp.)	0.235 (+0.1pp.)
	T1	0.053 (+1.1pp.)	0.071 (+0.3pp.)	0.168 (+0.0pp.)
	C1	0.033 (+1.2pp.)	0.034 (+0.3pp.)	0.121 (+0.0pp.)
Town	R	0.165 (+0.2pp.)	0.091 (-1.1pp.)	0.081 (-0.1pp.)
	T1	0.15 (-0.2pp.)	0.061 (-1.5pp.)	0.087 (-0.1pp.)
	C1	0.125 (-0.9pp.)	0.024 (-2.4pp.)	0.038 (-0.3pp.)
	T2	0.145 (-0.3pp.)	0.046 (-1.7pp.)	0.068 (-0.2pp.)
	C2	0.134 (-0.6pp.)	0.03 (-2.1pp.)	0.057 (-0.2pp.)
City	R	0.016 (+0.1pp.)	0.11 (+0.7pp.)	0.046 (+0.2pp.)
	T1	0.005 (-0.3pp.)	0.072 (+0.9pp.)	0.018 (+0.2pp.)
	C1	0.007 (-0.2pp.)	0.086 (+0.8pp.)	0.031 (+0.2pp.)
	T2	0.006 (-0.3pp.)	0.065 (+0.9pp.)	0.017 (+0.2pp.)
	C2	0.012 (0.0pp.)	0.091 (+0.8pp.)	0.032 (+0.2pp.)

Table A8: Predicted Math Test Scores, Z-Score

School Location	Age Group		
	Age [6,12)	Age [12,15)	Age [15,18]
	A. Baseline		
Rural	0.05	0.063	0.055
Town	0.036	0.031	0.034
City	0.032	0.026	0.027
	B. Edu. Expenses Subsidy in Rural Areas (20%)		
Rural	0.05 (-0.4%)	0.057 (-9.1%)	0.056 (+1.9%)
Town	0.036 (+0.0%)	0.032 (+3.9%)	0.034 (-0.5%)
City	0.032 (+0.4%)	0.029 (+11.4%)	0.027 (-2.6%)
	C. Edu. Expenses Subsidy at Destination (10%)		
Rural	0.037 (-25.4%)	0.063 (+1.0%)	0.055 (-0.2%)
Town	0.036 (-0.1%)	0.03 (-0.4%)	0.034 (0.0%)
City	0.041 (+26.2%)	0.025 (-1.3%)	0.027 (+0.4%)
	D. House Price Drop (Town: 15%, City: 10%)		
Rural	0.051 (+0.5%)	0.063 (+0.0%)	0.055 (+0.1%)
Town	0.036 (-0.1%)	0.031 (-0.1%)	0.034 (0.0%)
City	0.032 (-0.5%)	0.026 (+0.1%)	0.027 (0.0%)