School Restrictions, Migration, and Peer Effects: A Spatial Equilibrium Analysis of Children's Human Capital in China*

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Abstract

In China, policy restrictions hinder domestic migrant children from attending local public schools, compelling migrant children to enroll in subpar migrant schools and inducing parents to leave children behind in hometowns. Despite potential enhancements in educational quality for migrants, local parents and governments have resisted the relaxation of this enrollment restriction due to financial costs and fears of negative spillovers on local children, complicating the determination of the overall welfare effects. In this study, we investigate relaxing this policy in two steps. First, we identify the peer effects from migrant and left-behind children on their classmates and find that the negative spillovers from left-behind children are large but those from migrant children are modest. Second, we construct a spatial equilibrium model accounting for these peer effects and find that this policy relaxation can foster migration, elevate educational equality, and augment national human capital. Children of families from small cities benefit, but those from families in big cities lose due to short-run negative peer effects. The gains of parents and children are much larger than the financial cost. This is the first study to construct a unified framework to analyze the globally discussed migrant and left-behind children issue.

Keywords: Migration in China, Migrant children, Left-behind children, Migration restrictions, Spatial equilibrium

JEL Codes: I21, J61, R23

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1 Introduction

The modern spread of globalization has led to dramatic increases in international and domestic migration. This movement of people has sparked awareness of educational inequality and the low academic performance of migrant children compared with local children (Levels, Dronkers, and Kraaykamp, 2008; Schnepf, 2007). Data from the Programme for International Student Assessment (PISA) reveals that test score gaps between these groups can be as large as 10% in many OECD countries, which could later manifest as disparities in future earnings (Dustmann and Glitz, 2011). Migrant children face a dual challenge: the cultural adaptation and social integration process take time (Dustmann, Machin, and Schönberg, 2010), while they often attend lower-quality schools due to neighborhood segregation (Cascio and Lewis, 2012; Caetano and Maheshri, 2023). The financial costs of accommodating migrant children and the potential for negative peer effects spilling onto local children have led to backlash, including protests and political action from locals (Card, 2013; Ballatore, Fort, and Ichino, 2018). Another issue stemming from parental migration is the phenomenon of "left-behind children", who are not taken along when their parents migrate for work. The impact of parental absence on these children has been a subject of extensive discussion (Antman, 2013; Lyle, 2006). Various studies have explored this issue across diverse national contexts, such as Mexico (McKenzie and Rapoport, 2011), Tonga (Gibson, McKenzie, and Stillman, 2011), the Philippines (Cortes, 2015), China (Zhang et al., 2014), and El Salvador (Edwards and Ureta, 2003). This issue is a prevalent challenge in developing countries and has garnered significant attention from economists across the world.

Though migrant children and left-behind children can be considered two facets of a single issue—the impact of parental migration on children—existing literature tends to examine these two groups separately and there has been no research investigating them in a unified framework.

However, China presents a unique case where both groups coexist in substantial numbers, owing to the country's distinctive Hukou policy. In this study, we bridge this gap in the literature by offering a unified analytical framework that explores the educational outcomes of both migrant and left-behind children using Chinese data.

China has been experiencing a large wave of migration from under-developed to developed areas despite a unique household registration system, "Hukou," which deters migrant workers from fully accessing public resources in their destinations (Song, 2014). Specifically, students without a local Hukou are restricted from enrolling in local public schools, which are dominant in China (Hannum and Park, 2007). Nationally, although 70% of migrant children are registered in public school, the enrollment rate is highly heterogeneous across regions, falling as low as 20% in regions with large migrant inflows such as the Pearl River Delta (Yang, 2016). If migrant children are rejected by public schools, their only option is migrant-focused private schools, which are of much lower quality (Wang et al., 2017). Thus, a tough choice has to be made by migrant parents, either to take their children with them and risk rejection from a destination public school, or to leave their children behind to attend hometown public schools. Chen and Fu (2023) find that stricter enrollment policies have led to a notable increase in the number of parents choosing to leave their children behind. This creates de facto segregation in children's education in China. There were 103 million migrant and left-behind children in China in 2015, 30% more than all U.S. children. The education of this large group of kids will deeply affects the future of China.

The issue of migrant and left-behind children and the inequality in their educational opportunities remains a heated topic throughout China, debated by the mass media, scholars, and politicians for decades. Unsurprisingly, many studies have found that both migrant and left-behind students have poor cognitive achievement and school performance (Zhang et al., 2014), health outcomes and nutrition (Meng and Yamauchi, 2017), and emotional well-being

(He et al., 2012). Voices throughout China are advocating a relaxation of public school enrollment restrictions on migrant children and encouraging left-behind children to reunite with their parents (Chen, 2021). However, this would not come without cost. In many developed areas, parents are worried that inflows of disadvantaged migrant children would negatively affect local children. Local governments are also concerned about the costs of expanding public school capacity to accommodate migrant children. The conflict has become so intensive that in one major city, Suzhou, local parents built a wall to separate their children from migrant children attending the same campus (JingKids, 2018). The potential for negative spillovers and the related financial costs make estimating the overall welfare effects of this policy a subtle and complex exercise. The central government may face a tradeoff between the benefits accruing to children from migrant families and the costs experienced by local children and governments in more developed regions. Our study aims to assess the validity of these two concerns from parents and government, offering a nuanced, comprehensive analysis of the policy's overall benefits and drawbacks.

Our main research question is whether the public school enrollment restriction on migrant children should be relaxed. First, do children of migrant families really generate negative spillovers on their classmates? Second, accounting for peer effects, can we increase aggregate human capital by allowing more migrant children to enroll in local public schools in the destinations, and how much would this cost?

We answer these in two steps. First, we empirically identify the peer effects of migrant and left-behind students. Second, accounting for the peer effects, we construct a spatial equilibrium model of parents' and children's migration to evaluate the policy of relaxing enrollment restrictions on migrant students. We find that the negative spillover from left-behind students is large, while the spillover from migrant students is modest. By relaxing the public school enrollment restriction, China would substantially increase national human capital at an acceptable cost.

Families from small cities would benefit most.

In the first step of this paper, we estimate the peer effects of migrant and left-behind children. This is intrinsically tricky since the allocation of students across different classes and schools is usually not random. Students from advantaged families may sort into classes with fewer migrant and left-behind classmates. However, in China, middle schools are forbidden to assign students into classes based on their test scores or family backgrounds. For those schools which obey this law and assign students randomly into classes, we can identify migrant and left-behind students' peer effects using a simple regression with school fixed effects. We find that an increase of ten percentage points in the proportions of left-behind and migrant classroom peers on average reduce classmate standardized test scores by 0.088 and 0.038 standard deviations, respectively. However, one year later, the negative peer effect from left-behind children shrinks, and the negative peer effect from migrant children vanishes. These results alleviate the concerns of parents in developed areas and show that migrant children only have modest short-run negative spillovers which disappear with time.

In the second step, we construct a spatial equilibrium model to evaluate the costs and benefits of relaxing the enrollment restriction, taking peer effects into consideration. In the model, families are endowed with Hukou registrations in their hometowns and skill levels based on parental education. The household utility function includes wages, children's human capital, and unobserved location tastes. Children's human capital depends on peer effects from their migrant and left-behind classmates, whether they can enroll in public schools, whether they are left-behind or migrant, parents' wages, and location-specific shocks. Different locations have different public school enrollment probabilities, peer compositions, and school qualities. Parents need to choose which city to work in and whether to take their children with them if they migrate.

We estimate this model using various sources of data and implement several counterfactual analyses. In the main counterfactual, we relax the public school enrollment restriction on migrant children and find that it leads more children to migrate with their parents to large developed cities. Most importantly, the relaxation of the restriction increases aggregate human capital in three ways. First, children in private migrant schools can enroll in public schools with better quality after the relaxation. They are the directly treated group. Second, the relaxation of the restriction can promote human capital by encouraging more left-behind children to reunite with their parents. Third, the relaxation of the policy attracts parents who had initially stayed in hometown to migrate to big cities with their children. However, these increases do not necessarily translate into a net gain in overall human capital due to the presence of negative peer effects. There are winners and losers. Children from small cities benefit from the policy but children in larger cities with a higher concentration of migrant students would experience an average loss in human capital. To quantify this trade-off, we calculate national average human capital and predict an increase of 0.0077 standard deviations (as measured by cognitive test scores) if the enrollment restriction is totally removed. Specifically, for the directly treated group of children transiting from migrant schools to public schools (about 6% of the whole children population), their human capital increases considerably by 0.76 standard deviations. In a cost-benefit analysis, we find that the sum of gains in children's future income and parents' current utility is much larger than the financial cost paid by the government. When the restriction is wholly removed, the net gain (parents' gains + children's gains - government's costs) amounts to 363 RMB (54 USD) per student, or 35 billion RMB (5.2 billion USD) in total. The overall cost is 30 billion RMB (4.5 billion USD), equivalent to only 1.5% of annual government education expenditure. This is much smaller than one might expect. One key moderator of the cost is that although government has to fund new public school seats in big developed cities, they can reduce spending in small cities where the number of students shrinks.

This study contributes to three strands of the literature. First, though migrant and left-behind children are two facets of the same issue, they have been only separately discussed in previous literature across various countries (Dustmann and Glitz, 2011; Antman, 2013). However, analyzing them in a unified framework is crucial, as accurate policy analysis requires a general equilibrium setting with migration choice. Our study bridges this notable gap in the existing literature by offering a pioneering, unified quantitative analysis of educational outcomes for both migrant and left-behind children. It utilizes the unique context provided by China, where both groups exist in significant numbers due to extensive domestic migration and the special Hukou system. Additionally, it addresses an issue that has been a focal point in Chinese educational policy debates for decades (Zhang et al., 2014; Chen, Feng, and Han, 2019). We comprehensively investigate the costs and benefits of the public school enrollment policy which could guide future reform.

Second, many recent studies investigate migration and education choices using the tools developed in Eaton and Kortum (2002) and Ahlfeldt et al. (2015). This framework is also used in several studies of Chinese labor migration and its unique Hukou system (Tombe and Zhu, 2019; Ma and Tang, 2020; Tian, 2022; Fan, 2019). The focuses of these studies include regional inequality, trade liberalization, and spatial misallocation. Our study extends this EK-style spatial model by incorporating children's education and migration choices into a worker spatial migration model and attempts to provide some evidence for the dispute over public school enrollment restrictions for migrant children. In recent work, Sieg, Yoon, and Zhang (2023) investigate the impact of migration controls on urban fiscal policies and public services in China. The main difference relative to this study is that they focus on the fiscal policy implications of the Hukou system, not educational implications. In their model, children's human capital is totally determined by local public education spending and they do not consider, among other things, the costs of being left behind by migrating parents or the peer effects of migrant and left-behind children.

Third, this study utilizes a large-scale classroom random assignment of students to investigate peer effects. There have been many attempts to identify peer effects, though the endogenous nature of classroom grouping makes this very hard. Some approaches rely on small randomized controlled trials (Duflo, Dupas, and Kremer, 2011; Whitmore, 2005; Li et al., 2014; Graham, 2008). Others employ arguably exogenous variations or natural shocks (Hoxby, 2000; Ammermueller and Pischke, 2009; Imberman, Kugler, and Sacerdote, 2012). This study uses a nationally representative dataset and the fact that Chinese schools are required by law to randomly assign students into classes. Thus, the estimation in this paper is both internally and externally valid. Two recent studies (Hu, 2018; Wang, Cheng, and Smyth, 2018) use a similar strategy to estimate the peer effects of migrant students. Our study extends their work in three ways. First, we not only consider the peer effects of migrant children, but also left-behind children. Second, this study utilizes panel data, allowing for a thorough exploration of how these peer effects evolve over time. Third, a spatial equilibrium model inclusive of peer effects is developed, enabling the quantification of the impact of public school enrollment restrictions.

This paper is organized as follows. Section 2 provides the institutional background and describes the datasets. Section 3 provides empirical evidence on migrant and left-behind children's peer effects on their classmates. Section 4 develops a spatial equilibrium model with parents' and children's migration choices. Section 5 explains how the model parameters are identified and the estimation method. Section 6 conducts several counterfactual analyses. Section 7 concludes the study and discusses the policy implications for different countries.

2 Background and Data

2.1 The Hukou System and Left-behind Children in China

After the economic reforms in the late 1970s, China started to play an active role in international markets. Coastal provinces became the bases of the Chinese manufacturing industry and attracted an enormous amount of foreign investment. The reforms also triggered a large wave of migrant workers moving from under-developed inland areas to developed coastal areas. However, China's unique Hukou system served to systematically deter much migration. This system registers every household in China to their hometown and migrants without a local Hukou cannot fully access public resources in their destination cities. One of the most important resource restrictions is public school accessibility. By requiring housing ownership, proof of formal employment, or social insurance registration, public schools can deny children without a local Hukou. Migrant children often have to attend special private migrant schools, which are low quality (Wang et al., 2017). Figure 1 shows the fraction of migrant students enrolled in public schools by province in 2010. The red columns are developed provinces and the blue columns are under-developed provinces. In many developed provinces with more migrants, the enrollment probabilities are less than 75% or even 50%. According to Yang (2016), the overall enrollment rate in Pearl River Delta cities was 46% in 2015.[1] Specifically, in Dongguan, which is one of the largest manufacturing production bases and destinations of domestic migrants in China, the enrollment rate was as low as 23%.

These restrictive enrollment policies force migrant workers to make a difficult decision. They can either take their children with them and risk being unable to enroll their children in public schools. Or they can leave their children behind in their hometowns. These are migrant and left-behind children, respectively. The issue of left-behind children in particular has received much public attention. Living without their parents, they often suffer from physical and mental problems (Zhang et al., 2014; Meng and Yamauchi, 2017; Cameron, Meng, and Zhang, 2022). School enrollment policies are crucial in determining whether children accompany migrating parents or are left behind (Chen and Fu, 2023), and relaxing enrollment restrictions is an obvious response to mitigate this problem (Chen and Feng, 2013). However, attempts to relax restrictions

[1] Pearl River Delta is the manufacturing production base of China. It contains nine major cities, including Guangzhou, Foshan, Zhaoqing, Shenzhen, Dongguan, Huizhou, Zhuhai, Zhongshan, and Jiangmen.

often fail due to protests from local parents who believe migrant children will negatively affect their own children. Governments in developed regions also worry about the cost of providing enough public education if there are many migrant newcomers.

2.2 Education System and Classroom Random Assignment

The education system in China is different from most Western countries. Compulsory education lasts for nine years, including six years in primary school and three years in middle school. In this study, we consider only students in compulsory education. It is a predominantly public education system.[2] Although there were a handful of elite private schools in certain large cities, most quality schools were public.

School classes and the allocation of students to classes in China are also different. There is a general class for each student, and usually this class will take all their courses together throughout the middle school or primary school years. One teacher is appointed as the head teacher of the class. He or she will be responsible for overall academic performance and discipline. To maintain equality of opportunity, the Chinese government forbids all elementary and middle schools to assign students to classes according to their abilities or family backgrounds (PRC, 2006). While a few schools do violate the regulations and set up so-called "fast track" classes for elite students, in many Chinese middle schools students are randomly assigned to classes (Hu, 2018). We will use only these randomizing schools to identify peer effects.

2.3 Data

2.3.1 Data for the Estimation of Peer Effects

The dataset we use to estimate peer effects is the China Education Panel Survey (CEPS). It is a nationally representative panel dataset with two waves. In 2013, the survey interviewed 19,487

[2]According to the National Bureau of Statistics of China, in 2018 the total number of new students in middle schools was 16,026,000 and only 2,304,700 attended private schools, 12.5% of the total. Similarly, the total number of new students in primary schools was 18,672,970 and only 764,585 attended private schools, 3.9% of the total.

students from 112 middle schools across the country, with 10,279 from grade seven (class of 2016) and 9,208 from grade nine (class of 2014). In 2014, they followed up with students from the class of 2016, who were then in eighth grade. The class of 2014 was not included in the second wave since they had already graduated. The survey interviewed not only students but also their parents, teachers, and school principals, and contains information on whether students hold a local Hukou and whether they are living with their parents. We define migrant students as students without a local Hukou and left-behind students as students living without at least one of their parents.[3] We do not count students whose parents are divorced or died as left-behind. However, information on divorces and deaths is only available for the class of 2016. As a result, we drop all observations from the class of 2014 and use only the class of 2016. Further, as mentioned, there are many schools violating the law by arranging "fast track" classes for students with higher academic potential. Fortunately, the survey asks both school principals and teachers how schools assign students to classes. We cross-check these answers and keep only schools with "true" random assignment of students.

The *CEPS* also gave a standardized cognitive test to all students in both waves. This test comprises sections on language and reading, geometry and spatial reasoning, and computation and logic. It is designed to assess logical reasoning and problem-solving capabilities. We use the results from this test as the main dependent variable in the peer effects regression. As a robustness check, we also estimate them in regressions using traditional school-level test scores in Appendix A.1.

After cleaning missing data we have 10,443 observations. In the sample, after correcting for sampling weights, 13.0% of students are migrant students and 20.3% of students are left-behind students. These proportions are similar to those from the 2010 population census, indicating the dataset is close to be nationally representative.

[3]This is the definition usually used in previous studies. When we alter the definition of left-behind children to children living with neither parent, there is no significant change in the results. Please refer to Appendix A.1.

2.3.2 Data for the Spatial Equilibrium Model

In estimating the spatial equilibrium model, we additionally use a 0.35% sample of the 2010 *Census*. The *Census* is implemented every ten years and covers the whole population of China. Only very basic information is collected for 90% of households (short survey), while the remaining 10% complete a long survey with detailed demographic information on household composition, fertility history, and employment status. We utilize this long survey dataset to derive migration flows between different cities.

We use the Statistical Yearbooks of each city in 2010 to calculate the average wages of skilled and unskilled workers. These yearbooks record key city statistics each year, collected by local branches of the National Bureau of Statistics. Unfortunately, there is no direct city-skill-level wage data. Thus, we calculate city-skill-level average wages via city-industry-level average wages using the method in Fang and Huang (2022). The basic idea is to take the average of the city-industry-level wages, weighted by the proportion of skilled/unskilled workers in each industry in that city.

The public school enrollment probability is calculated from the *China Migrant Dynamic Survey (CMDS)* data in 2010. This is a survey covering migrant households, implemented by the National Health Commission. It contains information on migrant workers and their children's education. In this dataset there are 100,541 cross-city migrant families and 21,146 have at least one child of compulsory education age.

3 Peer Effects Analysis

3.1 Identification Strategy

The identification strategy for the peer effects is straightforward. In the main regression, we use the standardized cognitive test score implemented by the *CEPS* as the dependent variable y_{ijs}.

For student i in class j of school s, we have the following OLS regression:

$$y_{ijs} = \varphi_0 + \theta_1 Propmig_{-ijs} + \theta_2 Propleft_{-ijs} + \varphi X_{ijs} + \mu_s + \epsilon_{ijs} \tag{1}$$

where $Propmig_{-ijs}$ and $Propleft_{-ijs}$ are respectively the proportions of migrant and left-behind peers of student i in the class. These are leave-one-out measures, excluding student i. X_{ijs} is a set of controls, including year dummy, student, family, and teacher characteristics. μ_s is the school-level fixed effect. ϵ_{ijs} is the unobserved term. The peer effects we are interested in are θ_1 and θ_2. For schools which randomly assign students to classes, we can identify θ_1 and θ_2 by running regression (1).

We have information on whether the school implements random assignment of students from interviews of teachers and the principal in the *CEPS* data. We choose schools with (1) random assignment of new students in their first year; and (2) no reassignment of students in the second year. About 64 percent of the observations and 70 percent of schools meet these criteria. Table C1 in the Appendix shows summary statistics of the schools with and without random assignment. The categorical variable "school ranking" indicates the ranking of the school in its county. This is self-reported by the principal and the better the school is the higher the value is. This table shows that school characteristics are very similar regardless of classroom assignment rules and most of the differences are not statistically significant. Thus, the schools in the regression sample are still close to be representative.

3.2 Summary Statistics of the *CEPS* data

Some basic summary statistics are shown in Table 1. We define ordinary local (or in short, local) students as students who are neither migrant nor left-behind. Local students have parents with more education and they perform better on the standardized test. Left-behind children come from the most disadvantaged families. One concern is that the randomization may lead to minimal variation in the proportions of migrant and left-behind peers in different classes within a school, which may limit the statistical power. However, if the number of classes is not very small and the number of students in each class is not very large, there can still be sufficient variation. In our sample, we find that the average number of grade 7 classes in a school is 7, the average number of grade 7 students in a school is 358, and the average class size is 50. Figure 2 shows the distribution of the proportions of migrant and left-behind peers, which indicates enough variation exists in these two main independent variables. There is also a concern that migrant and left-behind children may not overlap with each other. Figure 3 shows the scatter plot of the proportions of migrant and left-behind peers across classes. Each dot represents a class in a school. There are many classes with both migrant and left-behind students. Typically, these schools are situated in the urban centers of small to medium-sized cities, which experience significant levels of both inbound and outbound migration.

3.3 Validation of the Randomization

The most important assumption for our identification strategy is that students are randomly assigned to classes within schools in our sample. We implement three steps to ensure proper randomization. First, we cross-check the responses of principals and teachers to the question of whether students are randomly allocated to classes in their schools and select only schools with consistent "Yes" answers to minimize the probability of misreporting.[4] Second, we turn to the literature using the same dataset and employing the same randomization (Hu, 2018; Gong, Lu, and Song, 2018; Xu, Zhang, and Zhou, 2022). Some other work uses different class-level independent variables such as teacher gender (Gong, Lu, and Song, 2018) or the proportion of low-ability peers (Xu, Zhang, and Zhou, 2022). They also find that these variables are not correlated with student characteristics. This also indicates that the classroom randomization in

[4]In the survey, they ask school principals what kind of student allocation rule they use. We consider only schools with random assignment. They also ask all teachers whether the school allocates students into different classes based on the test score of the subject they teach. We consider only schools without score-based assignment.

the *CEPS* does hold for the selected schools.

Third, we implement a balance check regression to investigate the correlation between student characteristics and the proportion of migrant and left-behind peers in his or her class. We regress the proportion of migrant and left-behind peers in a class on student and teacher characteristics. The characteristics include age, sex, whether this child lives at school (boarding), child's Hukou type (rural or urban Hukou), whether this child is a migrant student, whether this child is a left-behind student, whether this child is the only child at home, father's education, mother's education, parents' relationship, student's class ranking in sixth grade (the last year of primary school), whether his/her head teacher has a college degree, and head teacher gender. These variables capture various aspects of a student's family background, personal characteristics, and his/her teacher.[5]

Table 2 shows the results. In the first and the third columns, we run the regressions without controlling for school fixed effects. It is evident that there is a correlation between student characteristics and the composition of their classmates. For instance, students from families with higher parental education are in classes with fewer left-behind peers, which confirms school-level sorting. The F-test shows that the null hypothesis of zero joint effect for these variables is rejected. In the second and the fourth columns, we run the same regressions, additionally controlling for school fixed effects. This shows that almost all the correlations disappear once we use only the variation across classes within the same school, and the F-test shows that the null hypothesis of zero joint effect for these variables cannot be rejected, implying no evidence that classroom assignment is not random. In Appendix A.2, we extend the balance check in three specifications. First, we run these regressions separately for each independent variable. Second, we run these regressions separately for the 2013 and 2014 cohorts. Third, we run these

[5]One problem for the balance check is the mechanical sampling relation between the leave-one-out peer composition and the student's own characteristics. When calculating peer composition we exclude the student herself. Thus, the peer means can be a little different for each student in the same class, which is correlated with the student's personal characteristics. To solve this problem, we follow the suggestion from Guryan, Kroft, and Notowidigdo (2009) to further control for the school-level leave-one-out mean proportion of migrant and left-behind students in all the balance check regressions.

regressions by changing the dependent variable to the average ability of students in the class. We find no evidence of non-randomness in all these specifications.

3.4 Peer Effects Estimation Results

The mean and standard deviation of the cognitive test score y_{ijs} are 0.156 and 0.886. Table 3 shows the main results of the peer effects estimation. In column (1), we add student characteristics. In column (2), we additionally control for student household characteristics. In column (3), we further control for teacher characteristics. As the proportions are random, the differences in the point estimates across these three columns are small. The standard errors of the regressions are clustered at the school level.

The results show that both migrant peers and left-behind peers have negative spillovers on their classmates. Migrant peers have a modest effect. A ten percentage point increase in the proportion of migrant peers results in a 0.034-0.046 point decrease in a student's test score, which corresponds to a 0.038-0.052 standard deviation decrease. A ten percentage point increase in the proportion of left-behind peers results in a 0.078-0.098 point decrease in a student's test score, which corresponds to a 0.088-0.11 standard deviation decrease.[6]

In the main regression described in the previous paragraph, we pool data from both years together. We then investigate how the peer effects change over time. We keep only observations appearing in both years for comparability, which reduces the sample size. Table 4 shows the results when we run the regressions separately for the same group of students in their first year and second year of middle school. Interestingly, there are significant negative peer effects in the first year. However, in the second year, the negative effect from left-behind peers shrinks, and the negative effect from migrant peers vanishes. In all cases, left-behind peers have larger negative spillovers than migrant peers. The differences in the coefficients are statistically significant. It is

[6]This effect is relatively large compared with results from previous classic studies discussing the effects of other classroom variables on student performance. For instance, Krueger (1999) uses the Project STAR experiment in the U.S. and finds that a smaller class size (a decrease of the number of students in the class from 22—25 to 13—17) increases a student's test score by 0.19—0.28 standard deviations from kindergarten to the third grade.

likely that migrant students have only mild peer effects in general. As long as migrant students manage to adjust to their new classes, they will not negatively affect their classmates. This may alleviate concerns from local parents in developed areas. However, for left-behind students, even though their negative effects shrink in the second year, these effects are still economically and statistically significant. Living without parents and studying without careful supervision seems to have long-lasting harmful peer effects. In Appendix A.3, we further develop the heterogeneity analysis and find that children with low academic ability and children from families with poor parental skills are affected more severely, which is aligned with the findings here. In Appendix A.1, we implement several robustness checks. All results hold using different specifications.

In general, we have three main conclusions. First, left-behind students have negative peer effects on test scores. Second, migrant students have modestly negative peer effects. Third, in the second year of sharing a classroom, the modest negative effects of migrant peers disappear, and the negative effects of left-behind peers shrink. These regression results alleviate the worries of local parents in developed cities and support a relaxation of enrollment restrictions on migrant students. Further, if more parents take their children with them when they migrate, it not only benefits their children but also their children's former classmates. In Appendix A.4, we discuss one of the mechanisms of the peer effect. We find that the misbehavior of students is an important channel through which migrant and left-behind students negatively affect their classmates, especially left-behind students. Appendix A.5 discusses the selection concern that the larger negative spillovers of left-behind students only result from the fact that disadvantaged households are more likely to leave their children behind. We find that the family background of migrant and left-behind students accounts for only a portion of the observed peer effects, rather than explaining them in their entirety.

3.5 From Regression to Model

The single main policy question in this study is: should we relax the public school enrollment restriction on migrant children, and if so, how. There are two parts to this question. First, do migrant students produce negative peer effects on their classmates in developed cities, as their classmates' parents worry? Second, accounting for these negative peer effects, can a policy that relaxes the enrollment restriction on migrant children improve national human capital? If so, how much would government have to pay to relax restrictions compared with the gain?

We have empirically answered the first question, directly addressing the main reason why local parents are against relaxation. However, a simple regression analysis cannot directly answer the second question. Although relaxing the enrollment restriction could benefit migrant students, it could also (1) increase negative spillovers on children in developed areas in the short-run; (2) increase negative spillovers by encouraging more families to migrate. Further, relaxing the enrollment restriction means that local governments in developed cities have to build new or expand existing schools to accommodate new migrant students, which may be very costly.

We fully investigate the second question in a spatial equilibrium model in the following sections. This model explicitly takes the peer effects into consideration. The estimation of the peer effects parameters almost identically mimics our empirics above, except that we estimate the peer effects of migrant and left-behind peers on children from high-skill and low-skill families separately. Using this model, we implement the counterfactual of relaxing the enrollment restriction and conduct a cost-benefit analysis at the general equilibrium level. For the convenience of readers, we list notations and labels for all variables, parameters, superscripts, and subscripts used in the model in Tables 5 and 6.

4 Model

4.1 Basic Model Settings

The spatial equilibrium model is based on the traditional EK model (Eaton and Kortum, 2002) and extends it in two dimensions. First, we nest a workers' location choice EK model with another discrete choice over children's migration. Second, we incorporate children's human capital and education in the model.

The model is static and consists of two main parts.[7] Each worker is endowed with a Hukou registered in city i and some skill s. Workers with college diplomas (either two/three-year or four-year degrees) are considered high-skill workers (superscripted as h), and all others are considered low-skill workers (superscripted as l). There is an initial Hukou distribution $\boldsymbol{\Xi} = (\xi_1^h, \xi_2^h, ..., \xi_I^h, \xi_1^l, \xi_2^l, ..., \xi_I^l)$ of workers with different skills across the I cities in the country. A city means a prefecture, which includes a metropolitan area and its surrounding rural villages. In this model, workers are considered migrants if they work in a non-Hukou prefecture. Workers need to make two decisions, which city j to work in and whether to take their children with them when they migrate (if $i \neq j$). They value both final goods consumption and their children's human capital in their own utility functions. Consumption is determined by their wages in the local labor market. Children's human capital is determined by whether they can enroll in public school, the proportions of migrant and left-behind peers in their school (peer effects), whether they are migrant or left-behind, family income, non-schooling city fixed effects, and a stochastic shock. Children staying in their hometowns can always enroll in public schools. Migrant children are assigned a probability of being able to access public schools. Different cities have different public school enrollment policies, peer compositions, and school qualities.[8]

[7]Due to data availability and model tractability, a limitation of this study is that the model is static. It cannot capture the dynamic pattern of human capital accumulation. Thus, we underestimate the effect of relaxing the public school enrollment restriction and the counterfactual result is a conservative lower bound.

[8]Another limitation of this study is the assumption that public schools within the same city offer uniform quality of education. To keep the model tractable, we do not consider school district choices within cities. The "separate but equal" policy we investigate in Section 6.2 can be considered as a robustness check, illustrating a scenario where within city sorting perpetuates the segregation of migrant and local children.

The timeline of the model is as follows. First, workers choose a city to work in based on wages and their children's expected human capital. Second, children's unobserved human capital shocks realize. Third, workers make migration decisions for their children (to also migrate or stay behind) according to their expected human capital and the realized shock. The uncertainty in accessing public school is revealed after all decisions are made. We choose this sequential choice structure as most migrant workers in China move while their children are of pre-school age. We further discuss the robustness of this timing issue in Appendix B.14.

On the production side, each city has a firm with a CES production technology that converts a combination of high-skill and low-skill labor to final goods. The firm can hire workers from local labor markets, and the final goods market is perfectly competitive across the country. The labor market clearing condition determines the wages of workers with different skills in different cities, such that in each city, for each skill, the supply of labor equals the demand.

We illustrate the main mechanism of the model in Figure 4 using Shanghai as an example. Relaxing public school enrollment restrictions in Shanghai will first allow more migrant children currently living in Shanghai to access better education in public schools. This is the directly treated group. Second, this change will incentivize migrant parents to reunite with their previously left-behind children, which benefits not only their own children, but also their children's classmates in hometowns. Third, it will attract new migrants to Shanghai with their children. These three groups of new migrant students in Shanghai public schools may pose short-term challenges for local students through peer effects and increase the cost of education for local governments.

4.2 Utility

To abstract the model from labor participation decisions among parents, we assume that each family inelastically provides one unit of labor. For family (worker) o endowed with a Hukou in city i and skill s, he or she needs to choose (1) which city j to work in, and (2) whether to take his or her children to city j or leave them in hometown i. The utility function is as follows:

$$U_{ijo} = \frac{z_{ijo}}{\tau_{ij}^s} c_{ij} (u_{ij}^s)^\beta \tag{2}$$

$$c_{ij} = w_j^s \tag{3}$$

$$u_{ij}^s = e^{E[k_{ijo}^s]} \tag{4}$$

$$F(z_{ijo}) = e^{-z_{ijo}^{-\epsilon}} \tag{5}$$

where τ_{ij}^s is the migration cost for a worker with skill s migrating from city i to work in city j. When $i \neq j$, we define $\tau_{ij}^s = \bar{\tau}_i^s d_{ij}^*$, where $\bar{\tau}_i^s$ is the skill-home city fixed cost and d_{ij}^* is the home-destination migration cost. The migration cost differs across skills and captures three components: transportation cost, public service losses due to the Hukou system, and home bias. When $i = j$, there is no migration cost and $\tau_{ij}^s = 1$. c_{ij} is the consumption of final goods, which is determined by the wage w_j^s in city j. k_{ijo}^s is the human capital of children. Parents make their own migration decisions before their children's human capital shock. As a result, they consider their children's expected utility u_{ij}^s in their location choices with a weight β. z_{ijo} is the individual unobserved taste heterogeneity for different cities, following a Fréchet distribution, which is key in deriving the gravity equation. Parameter ϵ controls the dispersion of the shock.

4.3 Children's Human Capital

Based on migration choices, there are three types of families in this model. If the parents choose to stay in their hometown, they are "stayer" families, and their children are guaranteed local public school admission. If the parents migrate but leave their children, they are "left-behind" families. Their children can attend hometown public schools but bear a left-behind cost. If the parents choose to migrate together with their children, they are "migrant" families. Migrant children enroll in public schools or private migrant schools in the migration destination with some probability. These migration choices depend on human capital production and the shocks in different locations. Figure 5 shows the decomposition of the human capital equation.

Children's human capital k^s_{ij} consists of four components:

$$k^s_{ijo} = k^{*s}_{ijo} + \alpha w^s_j + t^s_{ijo} + \upsilon_o \tag{6}$$

where k^{*s}_{ij} denotes the schooling effect, capturing human capital that is related to education in school. αw^s_j denotes the family income effect on human capital (Dahl and Lochner, 2012). t^s_{ijo} denotes non-schooling human capital, which represents the effects of different cities on human capital beyond schooling, for example the effect of air quality. υ_o is the individual human capital shock with a type one extreme value distribution.

4.3.1 Schooling Human Capital Equation

There are two types of schools, public and private migrant schools. Let p^s_j denote the probability of enrolling in a public school in city j. We can write the schooling human capital equation as:

$$k^{*s}_{ijo} = p^s_j v^s_{ijo}(public) + (1 - p^s_j) v^s_{ijo}(private\_mig) \tag{7}$$

v^s_{ijo} is the human capital value obtained from attending either public or private migrant schools. Students with a local Hukou are guaranteed seats in public school. Therefore, $p^s_j = 1$ for both stayer and left-behind families. Migrant students without a local Hukou have some probability of enrolling in public schools. If unable, they have to attend private migrant schools. p^s_j is the key parameter measuring the severity of the enrollment restriction and we alter it in the main counterfactual analysis.

Given a type of school, the schooling human capital value is determined by the public school premium, left-behind or migrant cost, regional fixed effects, and school peer effects. For a child in family o with skill s attending school in region r, the schooling human capital production function is as follows:

$$v^s_{ijo} = \chi^s_0 + \mathbf{\Theta^s} Peer_o + \phi^s Pub_o + \nu^s lb_o + \eta^s mig_o + \kappa^s_r \tag{8}$$

$Peer_o$ is the peer composition in student o's class, which includes the proportions of migrant peers and left-behind peers. $\mathbf{\Theta}$ is the vector of peer effects. In private migrant schools, there are only migrant students. Pub_o is the public school indicator, which equals 1 if the school is public. ϕ^s is the public school premium. lb_o is the left-behind indicator, which equals 1 if o is a left-behind child. ν^s is the left-behind cost, which captures the depreciation of human capital when children live without their parents. mig_o is the migrant child indicator. η^s is the migrant child cost, which captures any human capital depreciation when children are away from their hometowns. κ^s_r is the regional fixed effect which captures differences in school quality across China. In the model, we divide the country into four regions according to the definition of the National Bureau of Statistics of China: Western, Middle , Northeastern, and Eastern regions. The Western region is taken as the reference group. All coefficients differ for families with different skills. We show the human capital production function for each specific type of family separately in Appendix B.1.

4.3.2 Non-schooling Human Capital Equation

When parents migrate for work, they can choose to take their children with them or leave their children behind. For simplicity, we assume that the non-schooling part of children's human capital in these two cases is as follows:

$$t^s_{ijo}(mig) = \zeta_{jm} + \zeta_s \tag{9}$$

$$t^s_{ijo}(left) = \zeta_{if} \tag{10}$$

ζ_{jm} is the city fixed effect of city j for migrants. ζ_{if} is the city fixed effect of city i for local Hukou holders, that is, left-behind children and children from non-migrant families. Both sets of fixed effects can be identified once we normalize ζ to zero for one of the cities (we choose Beijing as the reference). ζ_s represents the effects of migrating (compared with being left behind) on children for families with different skills. Let $V^s_{ijo}(Mig)$ and $V^s_{ijo}(Left)$ be the value functions of children who migrate and are left-behind.

4.3.3 Probability of Children's Migration

Denoting $exp(\cdot)$ as the exponential function, for workers who migrate, we can derive a closed-form function for the probability of children migrating with their parents:

$$V^s_{ij}(Mig) = k^{*s}_{ij}(Mig) + \alpha w^s_j + \zeta_{jm} + \zeta_s \tag{11}$$

$$V^s_{ij}(Left) = k^{*s}_{ij}(Left) + \alpha w^s_j + \zeta_{if} \tag{12}$$

$$Prob(mig) = \frac{exp(V^s_{ij}(Mig))}{exp(V^s_{ij}(Mig)) + exp(V^s_{ij}(Left))} \tag{13}$$

Furthermore, we can obtain a closed-form expected value for the human capital of children of migrant workers as:

$$\begin{aligned} u^s_{ij} &= exp[E[max\{V^s_{ij}(Mig) + \upsilon_{oj}, V^s_{ij}(Left) + \upsilon_{oi}\}]] \\ &= exp[ln[exp(V^s_{ij}(Mig)) + exp(V^s_{ij}(Left))]] \end{aligned} \tag{14}$$

When parents stay in their hometowns, there is no migration choice for children: they also stay in their hometown and attend public school. The expected utility with $i = j$ then degenerates to the following equation:

$$u^s_{ii} = exp[E[k^{*s}_{ii} + \alpha w^s_i + \zeta_{if} + \upsilon_o]] = exp[k^{*s}_{ii} + \alpha w^s_i + \zeta_{if}] \tag{15}$$

4.4 Gravity Equation

Given expected children's human capital, we then analyze parents' location choices. In this model setting, we assume a Fréchet distribution for the unobserved taste heterogeneity of workers across cities. For a worker endowed with skill s and home city i, we denote $\Phi_{ij}^s = (w_j^s (u_{ij}^s)^\beta)^\epsilon (\tau_{ij}^s)^{-\epsilon}$. One important property of this assumption is that it leads to a closed-form solution for the spatial distribution of workers across cities and implies a commuting probability equation as follows:

$$\pi_{ij}^s = \frac{\Phi_{ij}^s}{\Phi_i^s} = \frac{(w_j^s (u_{ij}^s)^\beta)^\epsilon (\tau_{ij}^s)^{-\epsilon}}{\sum_r (w_r^s (u_{ir}^s)^\beta)^\epsilon (\tau_{ir}^s)^{-\epsilon}} \tag{16}$$

where π_{ij}^s is the probability of a worker endowed with skill s and Hukou i migrating to city j. This is the gravity equation of the model. The derivation is standard and shown in Appendix B.2.

4.5 Production

To keep the model tractable, we assume that each city has a simple CES production function which takes both high-skill labor and low-skill labor as inputs. Final goods can be traded across the country in a perfectly competitive market and the price of the good is normalized to 1. The firm's optimization problem is as follows:

$$\max_{L_j^l, L_j^h} \quad y_j - w_j^h L_j^h - w_j^l L_j^l \tag{17}$$

$$y_j = [(A_j^h L_j^h)^{\frac{\sigma-1}{\sigma}} + (A_j^l L_j^l)^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}}$$

where A_j^h and A_j^l are high-skill and low-skill labor-augmenting productivities in city j. L_j^h and L_j^l are high-skill and low-skill labor demands. σ is the elasticity of substitution. Let $\rho = \frac{\sigma-1}{\sigma}$, the first order conditions are:

$$\frac{1}{\rho}[(A_j^h L_j^h)^\rho + (A_j^l L_j^l)^\rho]^{\frac{1}{\rho}-1}\rho(A_j^h L_j^h)^{\rho-1}A_j^h = w_j^h \tag{18}$$

$$\frac{1}{\rho}[(A_j^h L_j^h)^\rho + (A_j^l L_j^l)^\rho]^{\frac{1}{\rho}-1}\rho(A_j^l L_j^l)^{\rho-1}A_j^l = w_j^l \tag{19}$$

Dividing these two equations yields the skill premium:

$$(\frac{A_j^h}{A_j^l})^\rho(\frac{L_j^h}{L_j^l})^{\rho-1} = \frac{w_j^h}{w_j^l} \tag{20}$$

4.6 Spatial Equilibrium

We denote the vectors of the initial Hukou registration distribution in the economy as $\mathbf{\Xi}$, the public school enrollment probability as $\mathbf{p}$, labor augmenting productivity as $\mathbf{A}$, and migration costs between different cities as τ. We also denote the vectors of wages as $\mathbf{w}$, labor supply at equilibrium in different cities as $\mathbf{L}$, and peer compositions at equilibrium as **Peer**.[9]

We define the spatial equilibrium in this model as follows:

Definition 1 *Given the parameter vector* $\mathbf{\Gamma} = \{\beta, \epsilon, \alpha, \chi, \Theta, \phi, \nu, \eta, \kappa, \zeta, \sigma\}$ *and the city characteristics vector* $\mathbf{\Omega} = \{\mathbf{p}, \mathbf{A}, \tau, \Xi\}$*, the spatial equilibrium is achieved by the endogenous variable vector* $\mathbf{\Delta} = \{\mathbf{w}, \mathbf{L}, \mathbf{Peer}\}$ *that satisfies the following conditions:*

(1) Firms solve their profit maximization problems in equation (17); (Firm maximization)

(2) Workers choose locations and whether to take their children to migrate to maximize their utility; (Worker maximization)

(3) Labor supply equals labor demand in each city for both skill levels; (Labor market clearing)

(4) Workers perfectly expect the peer composition in each city. (Perfect foresight)

[9]As in many other urban economics models (Ahlfeldt et al., 2015), this model admits the existence of multiple equilibria. We discuss this problem in Appendix B.3.

4.7 Solving the Model

Given parameters $\mathbf{\Gamma} = \{\beta, \epsilon, \alpha, \chi, \Theta, \phi, \nu, \eta, \kappa, \zeta, \sigma\}$, data on the three endogenous variables $\mathbf{\Delta} = \{\mathbf{w}, \mathbf{L}, \mathbf{Peer}\}$ (wages, numbers of workers, and peer compositions in each city), data on the Hukou registration distribution of workers $\mathbf{\Xi}$, and data on the probability of entering public school in each location $\mathbf{p}$, we need to solve for the other two elements in the city characteristics vector, $\mathbf{A}$ and τ. Productivity $\mathbf{A}$ can be obtained from the first order condition of the firm profit maximization problem. The migration cost τ can be determined from the commuting probability equation. Appendix B.4 shows the detailed derivation of the equations.

5 Identification and Estimation

In this section, we explain how to calibrate and estimate this model. We also illustrate how each parameter is identified. First, we calibrate several parameters using widely accepted values from Chinese-focused literature, including the elasticity of substitution between types of skill σ, the family income effect on human capital α, and the dispersion of the Fréchet distribution ϵ. Then we identify and estimate the remaining ones in three steps. (1) We estimate parameters in the children's human capital function using student test scores in the *CEPS* data. These parameters are identified using variations in test scores across schools and students with different characteristics. (2) Non-schooling city fixed effects on children's human capital are estimated in a logit model using the *Census* data. These fixed effects are identified using variations in parent choices of whether to migrate with their children or leave them behind across different destination and home cities. (3) The weight parents put on children's human capital is estimated by running the gravity equation regression. It is identified by variations in parental migration choices over locations with different expected human capital and wages.

5.1 Calibrated Parameters

Several parameters are calibrated based on previous established literature. The elasticity of substitution between high-skill and low-skill labor is calibrated using the estimation in Katz and Murphy (1992), where $\sigma = 1.4$ and $\rho = 0.286$. Khanna et al. (2021) estimate the elasticity of substitution between high- and low-skill labor in China and find an identical value to that of Katz and Murphy (1992). The effect of family income on human capital is calibrated using the estimation in Dahl and Lochner (2012) and *CEPS* data, where $\alpha = 8 \times 10^{-6}$. The quantitative results are not sensitive to the choice of this parameter.[10] The dispersion of the Fréchet distribution ϵ is calibrated to be 1.5 as in Tombe and Zhu (2019) in a context of China. All calibrated parameters are summarized in Table C2.

5.2 Estimating the Schooling Human Capital Equation

In the first stage, we identify and estimate the schooling human capital equation (8) in two stages using data from the *CEPS*. In the first stage, we run a regression of student cognitive test scores on peer compositions, migrant and left-behind status, and school fixed effects:

$$v_o^s = \chi_0^s + \mathbf{\Theta}^{\mathbf{s}} Peer_o + \nu^s lb_o + \eta^s mig_o + \mu_o^s + e_o \tag{21}$$

v_o^s is the cognitive test score of student o from a family with skill s. χ is a skill-specific constant. $Peer_o$ is the proportions of migrant and left-behind peers in his/her class. μ^s is the school fixed effect, which contains the public school premium ϕ and the regional fixed effect κ. e_o is the error term. This regression is almost identical to the main regression in the section, except that we now estimate it separately for students from high- and low-skill families.[11] To alleviate the endogeneity issue and as discussed earlier, we use only those schools with random assignment

[10] Dahl and Lochner (2012) estimates that a 1000 USD increase in family income raises a child's test score by 0.06 standard deviations. We first translate USD to RMB, then calculate the corresponding α in our model based on the standard deviation of the *CEPS* cognitive test being 0.886. Our results are not sensitive to the choice of this parameter.

[11] Here we also control for student and family characteristics as in the empirical section. We do not control for teacher characteristics since this should be considered part of school quality.

of students to identify the peer effect. One concern here is that migrant and left-behind status are endogenous, as they may be correlated with unobserved family background and children's ability. Solving this problem without valid instruments is challenging, and we tackle it in several ways. First, we control for school fixed effects in this regression, which means that we are comparing students within the same school with similar family backgrounds. Second, we additionally control for student and family characteristics as in Section 3.4. We find that the addition of these control variables does not change the point estimates for the left-behind or migrant effects. Third, we test the sensitivity of our main counterfactual results by varying the parameters ν and η in Appendix B.13. This shows that the conclusions hold qualitatively across a range of calibrations.

In the second stage, we take the school fixed effects from the first stage and run the following regression to pin down the remaining parameters in equation (8):

$$\mu_o^s = \chi_0^{*s} + \phi_r^s Pub_o + \kappa_r^s + e_o^* \tag{22}$$

κ_r^s is the regional fixed effect based on school location. We can identify and estimate ϕ and κ in this regression. The standard errors are derived using the bootstrap method.

5.3 Estimating City Fixed Effects

In the second step, we estimate non-schooling city fixed effects on children's human capital in a logit model as in equation (13) using the *Census* data in 2010. These fixed effects are identified by variations in parental choices of whether to migrate with their children or leave them behind across different hometowns and destinations. The logic of the identification is as follows. As we normalize ζ_{jm} for Beijing to be zero, ζ_{if} for all other cities i can be identified by investigating the proportions of migrant and left-behind children for parents migrating from city i to Beijing. Similarly, as we normalize ζ_{if} for Beijing to be zero, ζ_{jm} for all other cities j can be identified by investigating the proportions of migrant and left-behind children for parents migrating from Beijing to city j. Since we have 276 cities, there will be $276 \times 2 = 552$ fixed effect terms. We utilize the algorithm recommended in Berry, Levinsohn, and Pakes (1995) to estimate the fixed effect terms. The detailed algorithm is described in Appendix B.5.

5.4 Estimating the Gravity Equation

The human capital coefficient β can be estimated using the gravity equation. From equation (16), we have:

$$\frac{\pi_{ij}^s}{(w_j^s)^\epsilon} = \frac{(u_{ij}^s)^{\beta\epsilon}(\tau_{ij}^s)^{-\epsilon}}{\Phi_i^s} \tag{23}$$

We have data on the migration flows between each pair of origin-destination cities for both high-skill and low-skill workers. We also calibrate parameter $\epsilon = 1.5$ as in Tombe and Zhu (2019). Then, we can derive the following regression to estimate β:

$$ln(\frac{\pi_{ij}^s}{(w_j^s)^\epsilon}) = \epsilon\beta lnu_{ij}^s + C_{is}^{'} + \xi_{ij} + err_{ij}^s \tag{24}$$

where $C_{is}^{'}$ is an origin city-skill level fixed effect and ξ_{ij} is an origin city-destination city fixed effect. err_{ij}^s is the regression error. The identifying variation comes from the fact that different destination cities have different attractions for children (u) from families with different skills (destination-skill-level variation). Parents are more likely to migrate to places with better education if they put more weight on their children (higher β).

5.5 Estimation Results

Table 7 shows the results from the first stage of the schooling human capital equation (21). For students from low-skill families, we find similar results as in Section 3.4: migrant and left-behind peers have negative impacts on their classmates and the negative effect from left-behind peers is larger. Meanwhile, for children of low-skill families, we also find a negative effect of being left behind by parents and no effect of migrating with parents. Due to a much smaller sample size, we do not have very precise estimates for high-skill children. However, the estimation of peer effects and the effect of being left behind are still negative. The only difference is that children from high-skill families are also negatively affected by migrating with their parents. Table 8 shows the results from the second stage of the human capital equation. Most of the coefficients are precisely estimated. We find a large positive public school premium, which shows their superior quality compared with private migrant schools. The public school premium is larger for high-skill families. We also find that schools in the Middle region are better and schools in the Northeastern region are worse than schools in the baseline region (Western).

Figure 6 shows the spatial distribution of the city fixed effects in non-schooling human capital ζ. Red means the value is larger and blue means the value is smaller. For both ζ_{if} and ζ_{jm}, the values in inland prefectures are larger than in coastal prefectures. This means that *except for* schooling, children build more human capital in inland regions. This implies better non-schooling factors in these regions such as better air quality. For the skill fixed effect, we find that $\zeta_f = 0.616$ and $\zeta_h = 1.876$. This indicates that high-skill families are more likely to migrate with their children compared with low-skill families.

Table 9 shows the results of estimating the gravity equation. The regression coefficient equals $\beta\epsilon$. As $\epsilon = 1.5$, we can derive that $\hat{\beta} = 0.96 \div 1.5 \approx 0.64$. In Appendix B.6, we calculate the willingness to pay for the public school based on this estimate of β, finding it implies that average low-skill Chinese parents are willing to pay about 13% of their annual wages to enroll their children in public schools. This translates to about 1,645 RMB or about 243 US dollars in 2010. As β is crucial in determining parent decisions on child migration, we use two other methods to further validate the estimation of this parameter. The first method is to calibrate β by matching the willingness to pay in the model to the school quality premium in the housing market from other literature. The second method is to implement a survey to directly ask migrant parents their willingness to pay for public schools and then match β to this stated preference, which provides direct evidence of the importance of public school enrollment to families. The details of these two validations are shown in Appendix B.7. We also check the sensitivity of the main results when β is changed in Appendix B.8. The main conclusions are not changed within a reasonable range of β.

After calibrating and estimating all the parameters, we run the model and calculate the equilibrium. We show the model fit in Appendix B.9. The model captures the main patterns in wages and migration quite well, which form our targeted moments. As an untargeted moment, we also check the model's "out-of-sample" prediction by comparing city-level relative output generated from the model to city-level GDP data. This further affirms that the model's fit is both robust and reflective of real-world conditions.

6 Counterfactual

In the counterfactual analysis, we evaluate how different policies can affect national human capital and carry out a cost-benefit analysis. The main counterfactual policy is to directly relax the public school enrollment restriction on migrant children. The detailed algorithm for solving the counterfactual is shown in Appendix B.10.

6.1 Relaxing Public School Enrollment Restrictions for Migrant Students

For the main counterfactual, we directly increase the probability with which migrant students can attend public schools and investigate how migration and human capital change. We set an enrollment probability floor $\bar{p}$, which forces all cities to enroll at least $\bar{p}$ of all migrant students in public schools. We then raise the probability from 72% to 100% and trace how family migration patterns and human capital change. We categorize the cities with most migrant students (95 percentile or higher) as big cities and the rest as small cities.

6.1.1 Family Migration

Figures C1 and C2 show the responses of parents' and children's migration. The red dashed line is the baseline level when the enrollment probability is not changed. Each blue dot represents a counterfactual value corresponding to a specific enrollment probability floor. Table C3 compares the original equilibrium and the counterfactual when we increase the enrollment probability floor to 88% and 100% in all cities. When the floor is set to 88%, about half of the cities are relaxing their enrollment restriction. The floor at 100% erases all enrollment restrictions.

In Figure C1 and Panel A of Table C3, we show the changes in parents' migration. When public school seats for migrant students increase, more families migrate for work since they are now more likely to enroll their children in public schools in their migration destinations. If the enrollment probability is increased to 88%, the model predicts a 1.2% increase in total worker migration, and a 2.4% increase when all enrollment restrictions are removed. In addition, high-skill migration increases relative to low-skill migration.

Figure C2 and Panel B of Table C3 offer a picture of how children move. As the enrollment restriction is relaxed, more families decide to migrate with their children, which results in more children in big cities and fewer in small cities. If the enrollment restriction is totally removed, the total number of students increases by 3.4% in big cities and the total number of migrant students increases by 9.5%. Given the Chinese population, we estimate that there will be in total 1.26 million new migrant students. The absolute number of students in big cities increases by about 0.57 million, which requires big cities to expand their public school systems by 13.6%. Meanwhile, more migrant parents choose to take their children with them, and the national ratio of left-behind students over migrant students decreases by 9.8%. In Appendix B.15, we investigate wage changes. Only high-skilled workers from big cities experience a decline in earnings due to an influx of similarly high-skilled workers. Conversely, all other groups see an increase in their wages.

6.1.2 Human Capital

Most importantly, we investigate the changes in human capital. Panel A of Table 10 shows the average changes for the directly treated group of children. This group comprises children who were previously enrolled in private migrant schools prior to the policy relaxation and have since transitioned to attending public schools. They benefit directly from the policy by enjoying better school quality and better peer quality. We find a large increase in human capital for these children. In general, sending children in private migrant schools to public schools can increase their human capital by about 0.76 standard deviations based on the cognitive test score. This is equivalent to an increase of 12 points on a 0-100 scale, exceptional progress in their academic performance.

However, there are winners and losers. Figure 7 and Panel B of Table 10 show that national aggregate/average human capital changes as the restriction is relaxed. Due to the negative spillovers from the inflow of migrant students, the human capital of students from big cities shrinks. In contrast, students from smaller cities with higher rates of out-migration experience significant benefits. Thus, this policy relaxation helps to shrink the education inequality between children from developed and under-developed regions. Panel B of Table 10 shows that national average human capital increases by 0.0077 standard deviations based on the cognitive test score when the restriction is totally removed. The national average change is notably more modest compared to the substantial increase observed in the directly affected group. This discrepancy arises primarily because the group of directly treated children comprises about 6% of the whole children population (though the absolute number of the directly treated children is still very large). Additionally, the policy's impact on indirectly affected children is not as pronounced as it is on those in the directly affected group.

6.1.3 Cost-benefit Analysis

We have shown that relaxing the enrollment restriction can help migrant children and increase national average human capital in China. However, this requires government to spend more money to expand public schools in certain locations. How expensive will this be? We examine the financial feasibility of this policy using a back-of-the-envelope calculation.

Financial data on Chinese compulsory education are only available at the provincial level for our calculations. We assume that the government keeps the quality of public education unchanged and spends the same amount of money for each newly enrolled migrant child as for current local children. In each equilibrium, we calculate total government expenditure by multiplying the number of students in public schools in each province by the expenditure per student in that province. The calculation of pecuniary benefit consists of two parts. First, parents' utility gain is recovered using the method described in Appendix B.6. Second, children's gain in terms of future income is calculated using a method similar to Krueger (1999). The detailed calculation process is described in Appendix B.16.

Figure 8 separately shows the average additional government expenditure, the average children's gain in terms of their future incomes, and the average parental gain in utility. Figure C3 shows the net gain, which is equal to the sum of parents' and children's gains minus government expenditure. We find that children's gains are large and parents' gains are relatively small. When the enrollment restriction is completely eliminated, the average gain for each family increases to 674 RMB. This is twice as large as the necessary government expenditure of 312 RMB. The total cost of removing the enrollment restriction is about 30 billion RMB (4.5 billion USD), which is only 1.5% of total government education expenditure as of 2010 in China. This is much smaller than one might expect. One important reason is that although government has to pay for new public school seats in big cities where students arrive, expenditures are saved in small cities where the number of students shrinks. Central government could finance the whole project by subsidizing local governments in developed regions using the savings from small cities. The net gain per student is 362 RMB when all migrant students are allowed to enroll in public schools. This amounts to total net gains of 35 billion RMB (5.2 billion USD). Appendix A.6 discusses the class size effect which may confound our cost analysis.

6.1.4 External Validity Concerns

An important concern in the counterfactual analysis is the selection of left-behind children and the external validity of the peer effects estimates. After the policy change, some stayers will migrate, and some families with left-behind children will reunite. These families may be disadvantaged and their children may have larger spillovers.

There are three responses to this. First, Figures 7 and 8 show that when the enrollment probability increases only marginally, in which case external validity should be a smaller problem, all conclusions are qualitatively the same. Second, in Appendix B.11, we try to alleviate the problem by adding the peer effects of students from high-skill families into the model. That is, the schooling human capital regression now includes the proportion of classmates from high-skill families as an additional term. All the results are very similar compared with the main setting. Third, in Appendix B.12, we amplify the peer effects of migrant students to equal those of left-behind students and re-calculate the counterfactual. In this setting, we effectively eliminate the human capital gain from spillover reduction. That is, even if left-behind children migrate to developed areas to reunite with their parents, they generate the same negative spillovers as before. This gives a lower bound estimate of the human capital gain. The results show that the relaxation of the restriction still increases human capital even in this worst case.

6.2 Additional Analysis

We consider counterfactuals in three additional alternative specifications.

First, in Appendix B.17.1, we implement a Chinese version "separate but equal" policy.

Instead of relaxing the public school enrollment restriction, the government takes over all private migrant schools and raises the quality of these schools to the level of public schools. We find that this "separate but equal" policy is less efficient than removing the enrollment restriction, even when we neglect the deep moral failures of such segregationist policy (Collins and Margo, 2006). Furthermore, for the sake of model tractability, we do not account for within-city school sorting in this model. Thus, this counterfactual also serves as a robustness check, representing a scenario where, after easing the enrollment restriction, migrant children only enroll in (sort into) public schools with a minimal number of local children.

Second, we consider long-run peer effects. In the main model, we use the peer effects estimates from the pooled regression in Table 7. However, we find the negative peer effects from migrant students disappear after two years. Thus, we re-calculate the main counterfactual when the peer effects of migrant students are reduced to zero in Appendix B.17.2. Under this scenario, the human capital gain is larger and the relaxation policy becomes a Pareto improvement. This result clearly shows the importance of helping migrant students adapt to their new lives as soon as possible. This also implies that our estimation of the human capital gain in this static model is a conservative one without considering the decay of the peer effect.

Third, we implement a channel decomposition in Appendix B.17.3. As illustrated in Figure 4, there are three key channels through which relaxing enrollment restrictions can elevate children's human capital. First, more current migrant children gain access to public schools with higher quality. Second, this relaxation enables many left-behind children to migrate to developed regions, reunite with their parents, and reduce their overall negative spillovers. Third, it motivates parents who have remained in their hometowns to migrate to developed regions along with their children. We find that the three channels contribute to the increase in human capital by 48%, 26%, and 26% respectively.

7 Conclusion

In this study, we provide the first analysis of the educational issues stemming from migrant and left-behind children within a unified general equilibrium framework. We evaluate the costs and the benefits of the controversial policy of relaxing the public school enrollment restrictions on migrant children in China, responding to concerns about negative spillovers and financial costs from local parents and governments in developed regions. By addressing one of the most pivotal debates in Chinese education policy in recent decades, we provide key policy guidance for potential reforms of the Chinese education system.

We show that the negative peer effect from migrant students is modest, but large from left-behind students. Within two years, the negative spillovers from migrant students vanish. In the counterfactual analysis, we find that although there are winners and losers, relaxing public school enrollment restrictions can encourage migration, promote educational equality, and increase national human capital. In the cost-benefit analysis, we find that the gain of this policy is twice the cost. The overall financial cost is only 1.5% of total annual government education expenditure, which is a manageable and worthwhile investment. Our study is the first quantitative investigation of China's public school enrollment policy, a major initiative that has far-reaching implications for millions of children. We recommend that the Chinese government further relax enrollment restrictions on migrant children, as such a move would yield long-term benefits for the nation as a whole.

Our study holds significant policy implications, not just for China but also for other nations. For developed countries such as the U.S., the U.K., Germany, France, and Italy, they host substantial numbers of children from international immigrant families who face a multitude of challenges—from cultural adaptation and language acquisition to school district segregation—that hamper their access to educational opportunities equivalent to those afforded to domestically-born children (Dustmann and Glitz, 2011; Dustmann, Machin, and Schönberg, 2010; Dos Santos and Wolff, 2011; Dahl et al., 2022). While our research emphasizes the critical need to minimize educational disparities between migrant and local children, it also draws attention to potential negative spillover effects on local student populations, as well as the financial burden borne by governments. Balancing these competing considerations represents a complex trade-off that governments of these nations will need to thoughtfully navigate.

For developing nations like India and Pakistan, which also experience substantial internal migration, the challenges mirror those in China; children from domestically migrating families often lack equal access to public educational resources compared to their local counterparts (Coffey, 2013; Dyer and Rajan, 2020). A UNICEF report indicates that as of 2011, India was home to a staggering 90 million migrant children (UNICEF, 2020). Despite the scale of this issue, it remains underexplored in mainstream economic research, and quantitative studies are notably scarce. While the barriers to education in India and similar countries may not be institutional in the same way as in China, our findings offer valuable insights that could serve as a springboard for future research aimed at understanding and addressing educational inequality between children of migrant families and local families.

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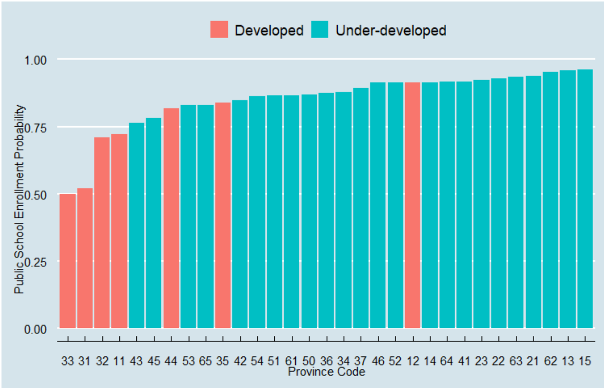


Figure 1: Public School Enrollment Probability by Province (2010)

Notes: This figure shows how public school enrollment probabilities vary across provinces. We define the top 7 provinces in terms of GDP per capita in mainland China as developed provinces. They are Beijing, Shanghai, Tianjin, Jiangsu, Zhejiang, Fujian, and Guangdong. These provinces are the top receivers of domestic migration. The developed provinces are colored red. Other provinces are green. Source: China Migrants Dynamic Survey 2010.

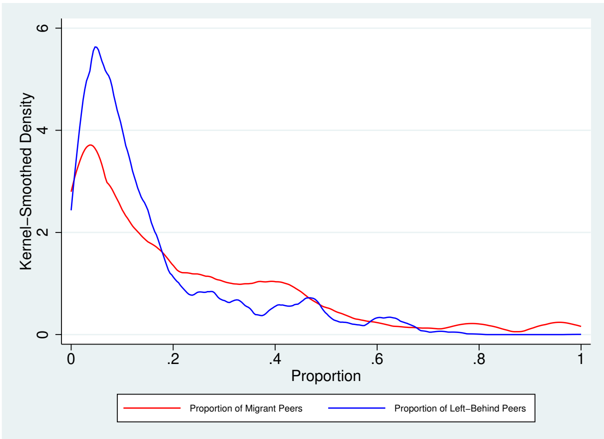


Figure 2: Distributions of Proportions of Migrant/Left-Behind Peers

Notes: This figure shows the distributions of the proportions of migrant/left-behind peers across classes. The red line shows the kernel-smoothed density of the proportion of migrant peers. The blue line shows the kernel-smoothed density of the proportion of left-behind peers. Sources: China Education Panel Survey 2013 and 2014.

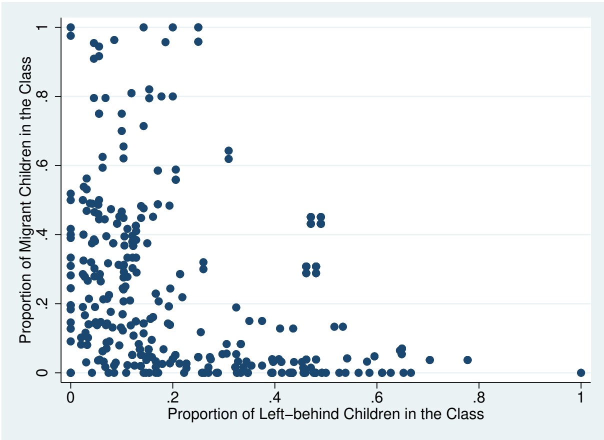


Figure 3: Scatter Plot of Proportions of Migrant/Left-Behind Peers in Each Class

Notes: This figure shows the scatter of the proportions of migrant and left-behind peers across classes. Each dot represents a class in a school. Sources: China Education Panel Survey 2013 and 2014.

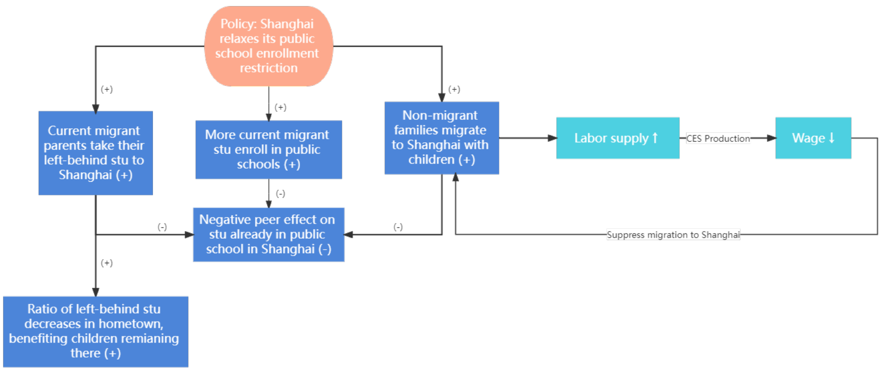


Figure 4: Counterfactual Mechanism Description

Notes: This figure describes the mechanism of the main counterfactual.

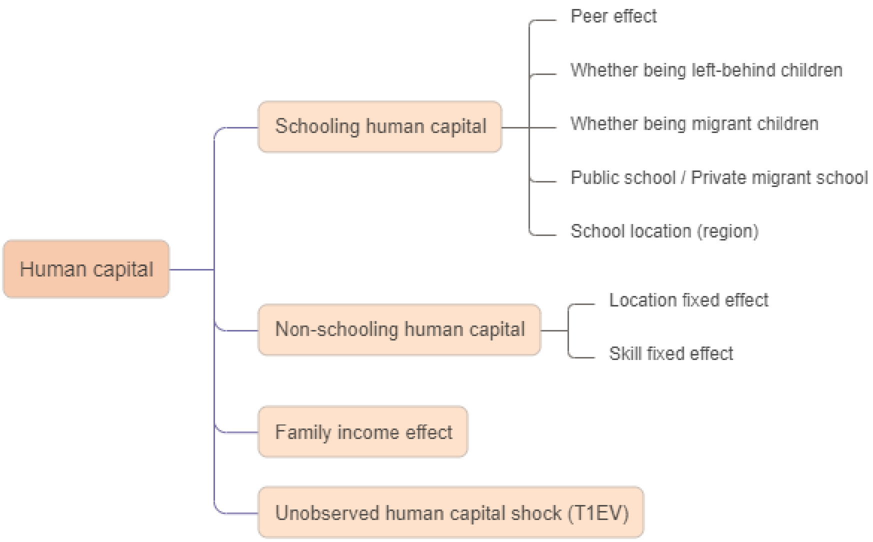
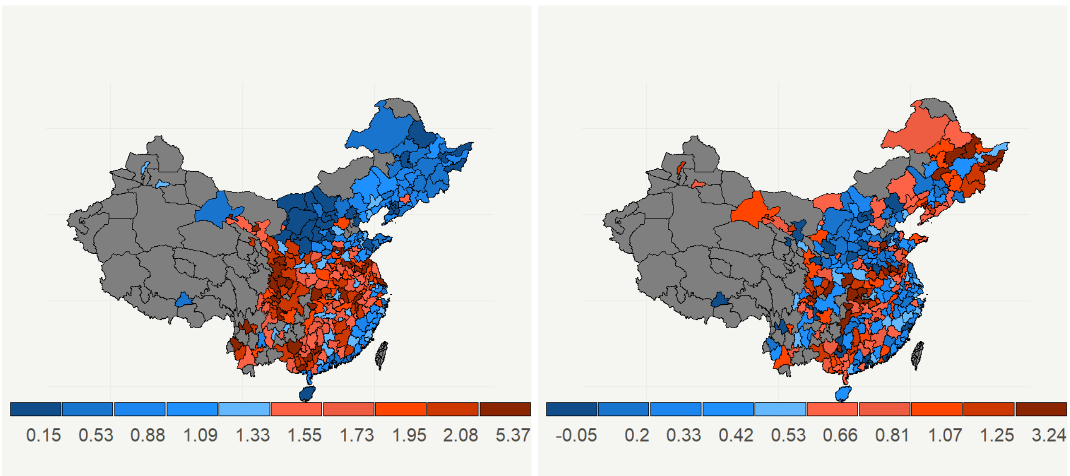


Figure 5: Human Capital Equation

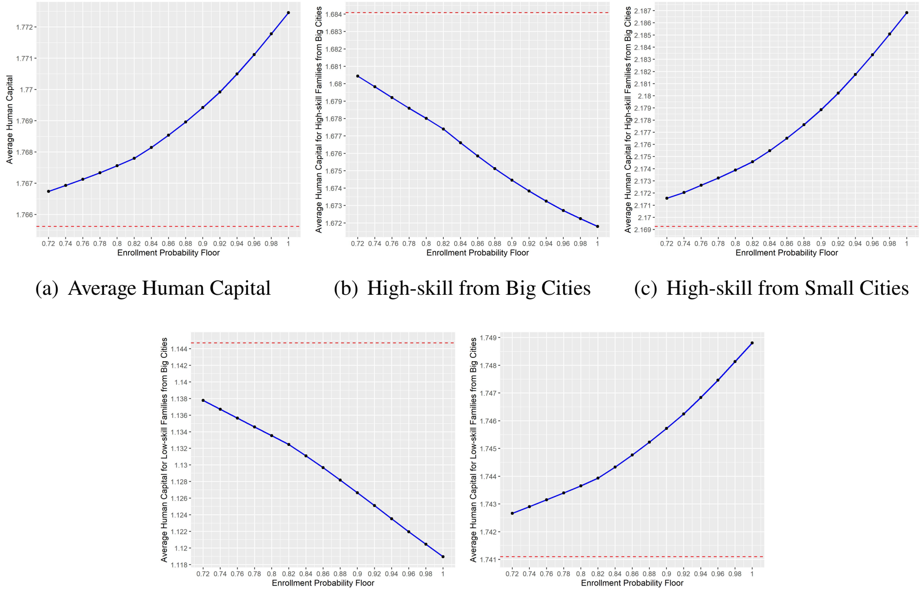
Notes: This figure shows the decomposition of the human capital equation.



(a) ζ_if (b) ζ_jm

Figure 6: Distribution of ζ Across Prefectures in China

Notes: This figure shows the geographic distribution of non-schooling city fixed effects on human capital. The color shows the magnitude of the fixed effects. Red means a larger value. Blue means a smaller value. Grey areas are prefectures (cities) with no data. These areas have very low population density. Sources: Census 2010, China Education Panel Survey 2013 and 2014.



(a) Average Human Capital (b) High-skill from Big Cities (c) High-skill from Small Cities

(d) Low-skill from Big Cities (e) Low-skill from Small Cities

Figure 7: Average Human Capital Changes with Enrollment Probability Increase

Notes: The x-axis represents the enrollment probability floor the government sets for each city. The blue dots with a solid line show the changes in average wages for different groups of workers as enrollment restrictions are relaxed. The red dashed line represents the baseline level with no relaxation of the enrollment restriction. Subfigure (a) shows the national average human capital. Subfigure (b) shows the average human capital for children of high-skill families from big cities. Subfigure (c) shows the average human capital for children of high-skill families from small cities. Subfigure (d) shows the average human capital for children of low-skill families from big cities. Subfigure (e) shows the average human capital for children of low-skill families from small cities. Sources: Census 2010, China Education Panel Survey 2013 and 2014.

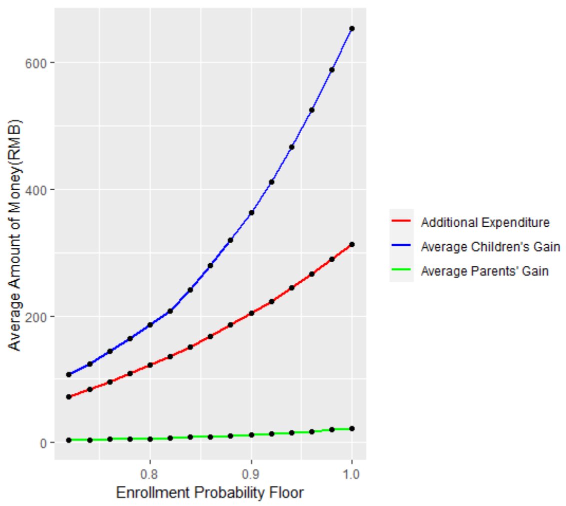


Figure 8: Average Costs and Benefits with Enrollment Probability Increase

Notes: The x-axis represents the enrollment probability floor the government sets for each city. The dots with a solid red line show the changes in average additional cost as enrollment restrictions are relaxed. The dots with a solid blue line show the changes in average children's gains as enrollment restrictions are relaxed. The dots with a solid green line show the changes in average parents' gains as enrollment restrictions are relaxed. All of the costs and benefits are measured by RMB. Sources: Census 2010, China Education Panel Survey 2013 and 2014.

Table 1: Summary Statistics

Variable	Migrant	Left-Behind	Local
Student Gender(=1 if boy)	0.530	0.551	0.502
	(0.499)	(0.498)	(0.500)
Student Age	12.969	12.988	12.926
	(0.849)	(0.940)	(0.824)
Student Hukou Type(=1 if rural)	0.600	0.629	0.399
	(0.490)	(0.483)	(0.490)
Father's Education Years	10.350	9.586	11.196
	(3.074)	(2.894)	(3.370)
Mother's Education Years	9.556	8.572	10.687
	(3.329)	(3.717)	(3.634)
Standardized Test Scores	0.158	-0.0779	0.261
	(0.861)	(0.889)	(0.853)

Notes: The summary statistics are calculated on the final sample using all schools with random assignments of students into classes. All the numbers without parentheses are mean values of the variable for the corresponding type of households. All the numbers with parentheses are standard deviations of the variable for the corresponding type of households. Sources: China Education Panel Survey 2013 and 2014.

Table 2: Balance Check

	Proportion of Migrant		Proportion of Left-Behind	
	Without School FE	With School FE	Without School FE	With School FE
Age	-0.00756	0.000476	0.0133*	0.000688
	(0.00742)	(0.000919)	(0.00782)	(0.00130)
Sex	0.0136**	0.00145	0.00552	-0.000376
	(0.00575)	(0.000942)	(0.00448)	(0.00109)
Board	-0.0214	-0.00856	0.0707**	0.000831
	(0.0305)	(0.00660)	(0.0286)	(0.00155)
Hukou Type	-0.0249**	-0.00227	0.0115	0.00280
	(0.0112)	(0.00354)	(0.00882)	(0.00352)
Whether Migrant Student	0.254***	0.0269	-0.0586***	-0.00734
	(0.0486)	(0.0229)	(0.0162)	(0.00469)
Whether Left-behind Student	-0.0269***	-0.00441	0.0957***	0.00564
	(0.00984)	(0.00360)	(0.0180)	(0.00617)
Only Child	0.0111	0.000406	0.0573***	0.000973
	(0.0172)	(0.00167)	(0.0109)	(0.00182)
Father's Education Years	-0.000253	-0.000292	0.0000513	-0.000450
	(0.00174)	(0.000406)	(0.00125)	(0.000353)
Mother's Education Years	0.000993	0.000237	-0.00660***	-0.000334
	(0.00162)	(0.000293)	(0.00106)	(0.000410)
Whether Parents Have Conflicts	-0.000568	-0.000434	0.0119	-0.000839
	(0.00658)	(0.00202)	(0.00782)	(0.00358)
Sixth Year Ranking	-0.000600*	0.0000667	0.000432	0.0000328
	(0.000334)	(0.0000537)	(0.000263)	(0.0000663)
Teacher Has College Degree	0.0204	0.0161	0.0110	0.0159
	(0.0191)	(0.0170)	(0.0209)	(0.0176)
Teacher Sex	-0.00159	0.00607	0.0340	0.0226
	(0.0184)	(0.0101)	(0.0232)	(0.0164)
School Fixed Effect	NO	YES	NO	YES
Year Fixed Effect	YES	YES	YES	YES
Observations	10,443	10,443	10,443	10,443
Joint F>Prob	0.000	0.429	0.000	0.893

Notes: In the first two columns, we run regressions for the proportion of migrant children on different variables with/without controlling for school fixed effects. In the third and the fourth columns, we run regressions for the proportion of left-behind children on different variables with/without controlling for school fixed effects. The coefficients in this table can be interpreted as the correlations between the independent variable and the composition of children in the class. All standard errors are clustered at the school level. Sources: China Education Panel Survey 2013 and 2014. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 3: Peer Effects of Migrant and Left-Behind Children on Standard Cognitive Scores

	(1)	(2)	(3)
Proportion of Migrant Peers	-0.456	-0.445	-0.337
	(0.278)	(0.273)	(0.242)
Proportion of Left-Behind Peers	-0.978**	-0.958**	-0.772**
	(0.441)	(0.433)	(0.347)
School FE	YES	YES	YES
Year Dummy	YES	YES	YES
Personal Controls	YES	YES	YES
Household Controls	NO	YES	YES
Teacher Controls	NO	NO	YES
Observations	10,443	10,443	10,443
R-squared	0.353	0.354	0.361

Notes: The dependent variable for all regressions is the standardized test score. In the main regression, we pool the data from two years together. For column (1), we do not control for household characteristics or teacher characteristics. For column (2), we do not control for teacher characteristics. For column (3), we control for all sets of variables. The set of personal controls includes student age, gender, Hukou type, whether he or she is a migrant student, whether he or she is a left-behind child, whether he or she is the only child, whether he or she lives at school, and his or her class rank in grade six. The set of household controls includes parental education, and whether their parents consistently have conflicts. The set of teacher characteristics includes whether the head teacher has a college degree and head teacher's sex. All standard errors are clustered at the school level. Sources: China Education Panel Survey 2013 and 2014. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 4: Peer Effects of Migrant and Left-Behind Children by Duration

	(1) First Year	(2) Second Year
Proportion of Migrant Peers	-0.507*	0.130
	(0.303)	(0.362)
Proportion of Left-Behind Peers	-1.114*	-0.697***
	(0.611)	(0.210)
School FE	YES	YES
Personal Controls	YES	YES
Household Controls	YES	YES
Teacher Controls	YES	YES
Observations	3,600	3,600
R-squared	0.390	0.403

Notes: The dependent variable for all regressions is the standardized test score. We keep only the observations appearing in both waves to make the regressions comparable in terms of the sample. For column (1), we use data from the first year. For column (2), we use the same group of students from the second year. The set of personal controls includes student age, gender, Hukou type, whether he or she is a migrant student, whether he or she is a left-behind child, whether he or she is the only child, whether he or she lives at school, and his or her class rank in grade six. The set of household controls includes parental education, and whether their parents consistently have conflicts. The set of teacher characteristics includes whether the head teacher has a college degree and head teacher's sex. All standard errors are clustered at the school level. Sources: China Education Panel Survey 2013 and 2014. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 5: List of Variables and Parameters in the Spatial Model

Notation	Label
Panel A. Variables	
U	Utility
u	Exponential of the expected human capital
k	Human capital of children
k^*	Schooling human capital
t	Non-schooling human capital
υ	Unobserved human capital shock (T1EV)
z	Utility shock (Fréchet)
τ	Migration cost
$\hat{\tau}_i^s$	Skill-home city fixed migration cost
d_{ij}^*	Home-destination specific migration cost
c	Consumption
w	Wage
p	Probability of public school enrollment
v	Human capital value of attending one type of school
V	Human capital value of migrating with parents or being left behind
$Peer$	Peer composition (Proportion of migrant and left-behind peers)
Pub	Public school enrollment indicator
lb	Left-behind children indicator
mig	Migrant children indicator
Φ_{ij}^s	The numerator of the gravity equation
Φ_i^s	The denominator of the gravity equation
y	Output
L	City-level number of labors
S	Share of number of migrant and left-behind children in a city
Panel B. Parameters	
β	Weights of children's human capital in parents' utility
α	Income effect on human capital
ϵ	The dispersion of the Fréchet distributed utility shock
χ	Skill-specific constant in schooling human capital
Θ	Peer effect in schooling human capital
ϕ	Public school premium in schooling human capital
ν	Left-behind effect in schooling human capital
η	Migrant effect in schooling human capital
κ	Regional fixed effect in schooling human capital
ζ_{jm}, ζ_{if}	City fixed effect in non-schooling human capital
ζ_s	Skill fixed effect in non-schooling human capital
σ	Elasticity of substitution of skills in the production function
ρ	Substitution parameter in the production function
μ	School fixed effects in estimating schooling human capital
e, e^*	Error in estimating schooling human capital
err	Error in estimating the gravity equation

Notes: This table reports all variables and parameters used in the spatial equilibrium model.

Table 6: List of Superscripts and Subscripts in the Spatial Model

Notation	Label
Panel C. Superscripts and Subscripts	
i	Hometown city (Hukou registered)
j	Destination city
s	Skill level
o	Family, individual, child
h	High-skill family
l	Low-skill family
m	Migrant family
f	Left-behind family

Notes: This table reports all superscripts and subscripts used in the spatial equilibrium model.

Table 7: Estimation of the Human Capital Equation: First Stage

	(1) High-skill	(2) Low-skill
Proportion of Migrant Peers θ_1	-0.281	$-0.411^{\dagger}$
	(0.680)	(0.266)
Proportion of Left-Behind Peers θ_2	-0.322	-1.003**
	(0.674)	(0.411)
Whether is migrant student η	-0.0869	0.0193
	(0.0776)	(0.0354)
Whether is left-behind student ν	$-0.0838^{\dagger}$	-0.0602**
	(0.0644)	(0.0296)
School FE	YES	YES
Year Dummy	YES	YES
Personal Controls	YES	YES
Household Controls	YES	YES
Observations	2,716	7,775
R-squared	0.372	0.314

Notes: The dependent variable is the standardized test score. For column (1), we run the regression on students from high-skill families. For column (2), we run the regression on students from low-skill families. The set of personal controls includes student age, gender, Hukou type, whether he or she is a migrant student, whether he or she is a left-behind child, whether he or she is the only child, whether he or she lives at school, and his or her class rank in grade six. The set of household controls includes mother's education, father's education, and whether parents consistently have conflicts. All standard errors are clustered at the school level. Sources: China Education Panel Survey 2013 and 2014. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, and $^{\dagger}p < 0.2$.

Table 8: Estimation of the Human Capital Equation: Second Stage

	(1) High-skill	(2) Low-skill
Whether is Public School ϕ	0.579**	0.222***
	(0.304)	(0.0737)
School in East κ_{east}	0.125***	-0.0809*
	(0.0557)	(0.0450)
School in Middle κ_{middle}	0.0522	0.187***
	(0.198)	(0.0399)
School in Northeast $\kappa_{northeast}$	-0.191*	$-0.104^{\dagger}$
	(0.135)	(0.0704)

Notes: The dependent variable is the school fixed effects estimated from the first stage. For column (1), we run the regression on students from high-skill families. For column (2), we run the regression on students from low-skill families. All standard errors are estimated using a bootstrap process. All stars are assigned based on the bootstrapped percentile confidence interval. Sources: China Education Panel Survey 2013 and 2014. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, and $^{\dagger}p < 0.2$.

Table 9: Estimation of Gravity Equation

Variables	OLS
Child's Utility (u_{ij}^{s})	0.960***
	(0.167)
Original-Destination City Fixed Effects	YES
Original City-Skill Fixed Effects	YES

Notes: The regression controls for fixed effects at the original-destination city level and original city-skill level. Source: Census 2010. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 10: Changes in Human Capital: Increasing Enrollment Probability for Migrant Students

Variables	Changes (Test Score s.d.)	
	88% Floor	Total Removal
Panel A. Directly Treated		
Average HC of High-skill	0.758	0.762
Average HC of Low-skill	0.762	0.766
Panel B. National Average		
Average HC	0.0038	0.0077
Average HC of High-skill from Big	-0.010	-0.014
Average HC of Low-skill from Big	-0.019	-0.029
Average HC of High-skill from Small	0.0094	0.020
Average HC of Low-skill from Small	0.0047	0.0087

Notes: "Big" means big cities and "Small" means small cities. In this counterfactual, we increase the enrollment probability for migrant students in each city. In the first column, we show the changes in human capital when the public school enrollment probability of migrant children in each city is required to be at least 88%. In the second column, we show the changes in human capital when the enrollment restriction is totally removed and all migrant students can enroll in public schools. Panel A shows the average changes for the directly treated group of families. This group comprises families whose children were previously enrolled in private migrant schools prior to the policy relaxation and have since transitioned to attending public schools. Panel B shows the national average changes. Sources: Census 2010, China Education Panel Survey 2013 and 2014.