Peer Effects of Migrant and Left-behind Children: Evidence from Classroom Random Assignment in China*

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Abstract

In this study, I investigate the peer effects of domestic migrant children and left-behind children on their classmates. Left-behind children are the children who are left in their hometown when their parents migrate. I exploit the large-scale random assignment of students into classes within schools in China to deal with the identification challenge due to the self-selection of students, which is rarely seen in other countries. Results show that an increase of ten percentage points in the proportion of left-behind peers and the proportion of migrant peers in the class results in a decrease of 0.12 and 0.06 standard deviations in a student's test score, respectively. However, the negative peer effects of left-behind peers are halved and the negative peer effects of migrant peers are totally erased in the second year. The reduction can be attributed to an improved class environment, such as students' relationships. Left-behind students' misbehavior due to the lack of parents' supervision may cause long-lasting damage and negative spillover. In addition, the indirect channel of family background of migrant and left-behind students explains only part of the peer effect. Relaxing the enrollment restriction of migrant students and encouraging migrant parents to take their children with them might reduce the overall negative spillovers.

Keywords: Peer effect, Domestic migration, Migrant children, Left-behind children, Migration restrictions

JEL Codes: I21, J61

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1 Introduction

Peer effects has been a heated topic in labor economics for years (Epple and Romano, 2011; Sacerdote, 2011). The research is closely related to the question of how policy makers should organize classes according to students' abilities, genders and races to achieve efficiency and fairness. However, some intrinsic difficulties in the identification of peer effects, including self-selection into schools and classes, makes it a very hard question when only observational data is available (Manski, 1993; Brock and Durlauf, 2001). The hardest part in identifying peer effects in classrooms is the non-randomness of school and class choices. Students of high socioeconomic status tend to study together with other students of high socioeconomic status. Traditional methods are either too costly (experiment) or not clean enough (fixed effects) because it is always very difficult to exclude all confounding factors by simply controlling for more and more variables. This research is one of the first studies to solve this problem by utilizing nationally representative panel data with random assignment of students into classes.

Policy debate on whether immigrant students can harm their local classmates is also catching people's eyes in many countries, especially during the refugee crisis. However, very little attention has been paid to domestic migrant students' peer effect. This study is also one of the first to incorporate the domestic migration question with peer effects.

In this paper, I exploit the random scheme in the assignment of students into classes and the huge number of migrants in China to investigate the peer effect of migrants' children. In China, middle schools are required by law to randomly assign students into classes. This special institution provides us with an excellent opportunity to identify the peer effect, which is not possible for previous studies in other countries. In addition, after China's economic reform, a gigantic wave of labor forces migrated from under-developed areas to developed areas.[1] This huge number of domestic migrants is also unique in the world, which makes it possible to study

[1] The number of children involved in the migration wave is now over 100 million. http://www.unicef.cn/en/uploadfile/2017/1009/20171009112814506.pdf

children from migrant families and their interactions with classmates. In general, China sets a perfect stage for studying the peer effects of students involved in migration.

As in many other developing countries (Cortes, 2008; Graham et al., 2012), some Chinese parents migrate to other places for work and leave their children at home. I call these children "left-behind children". In addition, I refer to children who migrate with their parents and go to schools in the migration destination as "migrant children". Because of the Hukou system,[2] migrant children may not be permitted to enroll in public schools in developed areas (Chen and Feng, 2013; Liang and Chen, 2010; Liang, Guo, and Duan, 2008), which is the main cause of the "left-behind children" issue.

It is widely believed that both left-behind children and migrant children are disadvantaged groups (Feng and Chen, 2017; Yang, 2016). Left-behind children have to live without their parents' help and supervision. The absence of their parents may lead to lower cognitive and non-cognitive skills (Li, 2019; Jiang and Yang, 2019), and some of the left-behind children are considered to be disruptive students and troublemakers in the class (Ye, 2011; Dong and Xie, 2010). On the other hand, migrant children have to struggle to adapt to lives and schools in developed areas. They are usually from lower socioeconomic backgrounds and considered introverted and self-abased (Wang and Lin, 2019). This gives rise to a concern that migrant children and left-behind children may negatively affect their peers in the classroom.

In this study, I utilize the random assignment of students into classes within schools in China and find that an increase of ten percentage points in the proportion of left-behind peers in the class reduces the standardized test score of a given student by 0.12 standard deviation. Meanwhile, an increase of ten percentage points in the proportion of the migrant peers in the class reduces the standard test score of a student by 0.062 standard deviation. As the classes in China are fixed in the three years of the middle school, I also estimate the peer effects in the same class over years. I find that the negative effects of left-behind peers are halved and the negative

[2]The Hukou system is a unique household registration system in China. I will describe it in detail in the following sections.

effects of migrant peers are totally erased in the second year. The reduction/disappearance of the peer effects on classmates' test scores may be attributed to the improvement of the class environment such as students' relationships and learning atmosphere. This confirms an assimilation story of the migrant students to the new environment. Additionally, I find that migrant students and left-behind students lack their parents' care and are more likely to be involved in misbehavior. They have a long-lasting effects on their classmates by increasing their classmates' misbehavior, which may explain the existence of left-behind peers' negative spillovers on their classmates' test scores in the second year.

These results imply that although there will be some detrimental effect of migrant students on their local classmates at first, it will disappear as they get along with each other and know each other well. Policy makers should help them to fit in the environment in developed areas. On the other hand, the negative effect of left-behind students on their classmates is much larger than the effect of migrant students, and it does not disappear in the second year. The absence of their parents results in a persistent damage, which calls for an urgent intervention of the government to take care of them when they are living without their parents.

I also claim that since the negative effects are larger and more persistent from migrant students than from left-behind students, we might reduce the negative spillover by relaxing the enrollment policy in developed areas to encourage parents to take their children with them. However, it is possible 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 and students from more disadvantaged families can have more negative spillovers on their classmates. If self-selection is the whole story, this policy will only transfer the negative spillovers rather than reducing them. I check whether this is the case and find that pre-determined family characteristics, such as the parents' education, is a part but not the only channel for the negative peer effects. Evidence points to a direct causal impact of migrant and left-behind status, which alleviates the external validity concern.[3]

Current literature employs several strategies to attack the self-selection problem in identifying peer effects. Some of them conduct randomized controlled trials (Duflo, Dupas, and Kremer, 2011; Li et al., 2014; Whitmore, 2005; Boozer and Cacciola, 2001; Graham, 2008), which are costly and locally. Some of them employ arguably exogenous variations across cohorts and classes within a school, or simply control for some fixed effects (Hoxby, 2000; Kramarz, Machin, and Ouazad, 2008; Lefgren, 2004; Ammermueller and Pischke, 2009).[4] The identification of these studies is usually not as clean as those experimental studies. Thus, there is a tradeoff between internal validity and external validity in previous research. My study instead uses a method that is both clean and representative.

The peer effects of immigrants on local students is well studied, especially in developed countries.[5] However, all of these works study international immigrants. Despite the much larger scale of domestic migration,[6] the only study concerning internal migrant students' peer effects is Imberman, Kugler, and Sacerdote (2012). However, their study still has some limitations,[7] and my research can improve the literature by employing the massive internal migration and the random assignment of students into classes in China.

There are some studies about migrant students and left-behind students in China.[8] The most relevant two studies are Hu (2018) and Wang, Cheng, and Smyth (2018), who study the peer effects of migrant students. My research extend their works in three dimensions. First, I consider not only migrant students but also left-behind students. This is very important since migrant par-

[3]Huang (2020) investigates this question by employing a spatial equilibrium model. He shows that we can increase the human capital of the society by removing the public school enrollment restriction on migrant children.

[4]The only study using nationally representative data with random assignment of students into classes to tackle the peer effect outside China is Kang (2007), which uses data from South Korea. However, he has only cross-sectional data and does not solve the reflection problem.

[5]For instance, Card (2013); Cascio and Lewis (2012); Ohinata and Van Ours (2013); Gould, Lavy, and Daniele Paserman (2009); Ballatore, Fort, and Ichino (2018); Tonello (2016) and Geay, McNally, and Telhaj (2013).

[6]According to the data from CPS, in the U.S., the total number of domestic migrants in 2019 is 30.2 million and the total number of immigrants from other countries is 1.1 million. See https://www.census.gov/data/tables/time-series/demo/geographic-mobility/historic.html

[7]First, the group of migrants in their study is refugees of a natural disaster (Hurricane Katrina), which is totally different from the usual group of migrants who choose to migrate by themselves. Second, they admit that they cannot fully rule out channels affecting students' performances other than through the change of their peers' qualities (for instance, the sudden arrival of evacuees also changes class sizes).

[8]Most of the studies focus on migrant and left-behind students' disadvantages on their studies and health. See, for instance, Zhang et al. (2014); Meng and Yamauchi (2017) and Chen (2013).

ents may change their choices of whether to take their children with them, as the government changes policies. Second, they use only cross-sectional data, but I have panel data. Thus, I can investigate the evolution of the peer effects across time and consider the mechanism driving the elimination of the effects across time.[9] Third, they use school-level Chinese/Math/English test scores as measurements of performances. Those tests are not comparable across schools, which can bias the results.[10] I instead use a standard cognitive test score, which is comparable for students from different schools across the country.

My research also extends the literature discussing the assimilation of migrants to the migration destination. These studies are led by some early works like Chiswick (1978), Long (1980) and Borjas (1985). They concentrate on immigrants' improved performances in the labor market across time.[11] My paper provides some evidence for the assimilation of migrants from another perspective.

Generally, there are three contributions of this research. First, this is one of the first studies using a random assignment of students in classrooms to solve the sorting issue in the identification of peer effects with panel data. Second, this is one of the first studies concerning the peer effects together with domestic migration. Third, this is the first study not only focusing on migrant students, but also taking left-behind students into consideration, thereby offering a broader picture of the migration policy.

[9] It is also important in the sense that the elimination of the peer effects can explain the discrepancy of the results in these two studies. Hu (2018) finds some negative spillovers from migrant students. However, Wang, Cheng, and Smyth (2018) find zero spillover using the same method. The reason is that Wang, Cheng, and Smyth (2018) use only observations from the ninth grade, when students have studied in the same classroom for two years and the negative peer effects have been eliminated.

[10] More details for why it may bias the causal effects are shown in Section 2.3.

[11] There are many works after these initial studies. Please refer to Dustmann and Glitz (2011).

2 Background and Data

2.1 The Hukou System and School Enrollment Restrictions

The Hukou system is a special household registration system in China.[12] All Chinese families have to register in this system according to where they live and where they are originally from. It is hard to change the registration place during one's lifetime. The Hukou registration place determines whether a household has full access to the local public resources. For instance, if a household registers their Hukou in Guizhou (which is a poor province in the Southwestern China), even though they can go to Beijing for work, they have limited access to public medical insurance and pension system in Beijing.

The inequality between native and non-native residents is noticeable in terms of education opportunities. First, public schools are dominant in China and non-native residents are restricted to enroll in public elementary and middle schools. Usually, the local governments set several standards for households with non-local Hukou if they want to send their children to public schools, including certification of permanent residence (for instance, living consecutively within the school district for at least one year) and stable jobs of parents (for instance, working consecutively in the district for at least one year). Due to the nature of migrant workers, they are likely to change their addresses and jobs often. As a result, many of them cannot meet the standards and send their children to local public schools in developed areas. According to the data of China Migrants Dynamic Survey in 2013, in advanced provinces with the largest number of migrants, such as Guangdong and Zhejiang, the probabilities for migrant students to enroll in public schools are lower than 70 percent. If they cannot get into public schools, migrants have to enroll their children in special migrant schools in developed areas, which are not of good quality (Feng and Chen, 2017).[13] Thus, migrant parents have to choose between either leaving

[12] For more details, see Cheng and Selden (1994) and Chapter 4 in Lin (2011).

[13] Wang et al. (2017a) and Wang et al. (2017b) find that the performance of migrant students in private migrant schools in cities is worse than performance of students studying in public schools in rural areas, and the gap will widen the longer they study there. Additionally, Lai et al. (2014) claim that the longer the migrant students stay in migrant schools in Beijing, the worse their academic outcomes will be.

their children back at home (left-behind children) to go to public schools there, or taking their children with them to developed areas (migrant children) and running the risk of being refused in the enrollment of public schools. According to the 2015 Census, the number of left-behind children is close to 70 million and the number of the migrant children is approximately 34 million (Duan, Lai, and Qin, 2017; Lv et al., 2018). Second, in most of the developed provinces, non-native students are restricted in taking the High School Entrance Exam (HSEE) and the College Entrance Exam (CEE). They are not allowed to apply for local public high schools in some big cities.[14] As a result, students can only take the CEE in their home provinces. These two characteristics of the institution in China lead to a *de facto* segregation in education between local Hukou students and migrant students.

2.2 Random Assignment of Students

In China, the organization of middle school education is different from most of the systems in western countries. During the three years of middle school, there is a "general class" for each student. Students in the same class will have all courses together and attend extracurricular activities as a group. Members of the class will not change during the three years.[15] There is a head teacher in charge of each class, who usually teaches one of the main courses (Chinese, Math, English or Science) for that class. This head teacher is responsible for not only the performance of the class on his or her own subject, but also the general performance of the class on all other subjects.

To solve the self-selection problem, I utilize the fact that within most schools in China, the assignment of students to classes is random. Although students can still select themselves into different schools by changing their residing school districts within a city, the Chinese government forbids any kind of ability tracking or sorting into classes according to the family back-

[14] The high school application and admission system is centralized at city level and the admission depends only on the score of the HSEE. In some big cities, migrant students are not allowed to apply for public high schools, which are considered to be the only way to get into college in the future. The college application and admission system is centralized at province level and the quota of each college in each province is fixed according to the number of Hukou registered students.

[15] In my data set, less than 0.1 percent of the students change their classes within a school.

ground of students within a school.[16] Although there are violations, the implementation of this law is restrictive in most places. Two methods of student assignments prevail: random scheme and average assignment scheme. The random scheme is simply assigning students randomly to various classes when they enter the school. The average scheme is a stratified random assignment method that aims to distribute students evenly to classes in terms of their abilities. The process can be described as follows. First, the school will organize an entrance exam for all of the new students. Then, students will be stratified into N tiers according to their exam scores. Tier 1 students are the students with the best scores and tier N students are the students with the worst scores. After that, each class randomly picks the same number of students in each tier, which keeps the ability distributions identical across classes. Both of the two schemes can keep the assignment process random.

2.3 Data

In this study, I use China Education Panel Survey (CEPS) data, which includes two waves, one in the 2013—2014 academic year (in short, 2013) and another one in the 2014—2015 academic year (in short, 2014). In 2013, the survey includes 19,487 students from 112 junior schools all over mainland China, with 10,279 from grade seven (class of 2016) and 9,208 from grade nine (class of 2014). In 2014, they track students from the class of 2016, who are in the eighth grade at that time. However, they do not track students from the class of 2014 since they have already graduated. In the main part of this paper, I use only students from the class of 2016 due to some data restrictions, which I will explain later. They interview students, their teachers, their parents and principals from all the schools. In the interview, they ask questions about the Hukou registration information of the students and their parents, and also whether students are living with their parents. Consequently, I define migrant children as students who are not living in their Hukou registered place and left-behind children as students who are not living together

[16] See the Compulsory Education Law of the People's Republic of China, http://www.npc.gov.cn/wxzl/gongbao/2015-07/03/content_1942840.htm

with at least one of their parents.[17] Children could also live without parents because of parents' divorce or death. I exclude such children from the definition of being left-behind. However, the survey does not ask questions about parents' marital status and whether they are still alive in the first wave. Thus, I have to use the information in the second wave to infer the marital status and whether the parents were alive in the first wave. As the students from grade nine in the first wave (class of 2014) are not included in the second wave, I have to drop all of them.[18] Furthermore, the survey also asks (anonymously) principals and teachers questions about the method of students' assignment into classes, which means that I can pin down which schools are actually implementing the random assignment of students.

In this survey, they also give a standardized cognitive test, which evaluates the cognitive skills of students. I use the results from this test as the dependent variable y in the regression instead of the school-specific Chinese/Math/English test scores used in previous studies. School-specific test scores are derived from exams implemented by each school separately, and the raw scores of these exams are not comparable across schools. In essence, traditional school-specific standardized scores are relative rankings within schools. On the contrary, the standardized cognitive test implemented by the survey is identical for students in various schools and districts, which is a ranking of the students from the whole country.

Most importantly, the usage of national-level standardized cognitive test score can avoid bias in identifying the peer effect. The reason is that the variations of the dependent variable (the proportions of left-behind and migrant peers in a class) I am using are also at class-level within schools. Given a school, an increase of the proportion of migrant/left-behind students in a class mechanically means a decrease of the proportion of migrant/left-behind students in other classes since the total number of migrant/left-behind students is fixed in this school. Meanwhile, the

[17] I also redefine the left-behind children as children who are living with neither of their parents. The results are shown in Section 6.

[18] One concern is that there may be changes in parents' marital status from the first wave to the second wave, which results in a measurement error when I impute the marital status of the first wave by the second wave. Thus, I redefine left-behind students without excluding these ones with parents' divorce and death and run the same regressions. The results are similar. I also run main regressions using samples from both class of 2013 and class of 2014 in this alternative definition of left-behind children. The results are not changed.

traditional measurement of school-level score is a relative ranking within the school and an increase of the performance of a student in one class means a decrease of the performance of a student in another class of the same school. Then the effect of the proportion of migrant/left-behind peers on a student's ranking within his or her school would be not only the direct peer effect in his or her own class, but also the indirect effect due to the change of proportions in other classes, which may magnify the estimates. For instance, we assume that there are two classes A and B in a school. An increase in the proportion of migrant peers in class A can affect class A students' school ranking by affecting their "performance" (real peer effect). In the same time, it will also mechanically reduce the number of migrant students in class B, which can affect class B students' school ranking. The ranking is relative, which means that the second channel can also alter the ranking of students in class A, which contaminates the real peer effects we want to capture.

To make my results comparable with previous literature, I also run *all* regressions in this paper using traditional school-level scores (Chinese, Math and English) as the outcome variable.[19] No qualitative conclusion is changed.

3 Empirical Strategy

3.1 Identification with Randomization

Consider the following OLS regression:

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

where $Propmig_{-ijs}$ and $Propleft_{-ijs}$ are respectively the proportion of migrant peers and left-behind peers of student i in class j of school s. They are leave-one-out measures, excluding i

[19] I show the main one in Section 6. The remaining regressions are available upon request.

him/herself.[20] X_{ijs} is the set of controls such as student's characteristics and family characteristics. μ_s is the school-level fixed effect. ε_{ijs} is the unobserved term. The dependent variable y_{ijs} is the standard test score of student i. The peer effects we are interested in are θ_1 and θ_2.

There is a typical endogenous self-selection problem when the assignment of students into classes is not random.[21] For instance, students from better socioeconomic backgrounds may cluster together. As a result, students in classes with high proportions of left-behind peers are likely to come from low socioeconomic backgrounds.

To solve the sorting problem, I use the random variation of proportions of migrant and left-behind students across classes within a school. For a given school, the class-level variation is created by the random assignment of students, which means that students can only sort themselves into different schools but not different classes in the same school. As long as I investigate the problem using data from schools with random assignment of students into classes and control for school fixed effects, the proportions of migrant students and left-behind students in the class will be random. Consequently, I can identify the peer effects neatly.

In practice, I set up three criteria to keep schools with random assignment of students. First, they should have a random class assignment when new students enter the school. Second, they should not reassign students in their second year according to their performances. If some schools have random assignment of students in their first year, but reassign them in the second year (based on abilities), I will drop the second wave of the students from these schools and keep the first wave. Third, the school should not implement ability tracking in specific subjects. For instance, some schools assign student randomly into classes but reassign students for some specific courses such as math. In these schools, students will have all classes other than math with their randomly assigned classmates, but have math classes with another group of peers assigned based on their math scores. I will exclude this kind of school. About 64 percent of

[20] I also run the regressions using the proportions of migrant and left-behind students of the whole class including student i him/herself as a robustness check. The results are almost the same.

[21] Details about the fundamental challenges in identifying peer effect model can be found in Sacerdote (2011); Epple and Romano (2011); Manski (1993).

the observations and 70 percent of the schools meet all the three criteria. Table 1 shows some summary statistics of the schools with or without random assignment of students into classes. The categorical variable of school ranking means the ranking of the school in the local county. It is self-reported by the principal and the better the school is, the higher the value will be. The table shows that most of the school characteristics are very similar and the differences are not statistically significant. Thus, the schools in the sample are still representative.

After cleaning some observations with incomplete information further, I have a data set with 11,519 observations. I do not use an individual-level fixed effect model, since in China, usually class members will not change during the three years in the middle school. It means that the variation of proportions of migrant peers and left-behind peers will be very small for the same student across the two waves.[22]

3.2 Summary Statistics

In the sample, after correcting for sampling weights, I find 13.3 percent of students to be migrant students and 20.3 percent of students to be left-behind students, which is similar to the figures from the 2010 population census, which means that the data set is nationally representative.[23] I run all regressions in this study with survey sampling weights.[24]

Some other basic summary statistics are shown in Table 2. I define ordinary local (or in short, local) students as students who are neither migrants nor left-behinds. The distributions of family backgrounds of left-behind students, migrant students and local students are different. For instance, local students are from families with the highest parents' education levels and left-behind students are from families with the lowest parents' education levels. Socioeconomic condition is a self-reported measure of socioeconomic status of the family, scaled from 1 to 5, with 5 as the highest. It is clear that left-behind students are from families with lower socioe-

[22]We can see some variations for the same class across waves, but most of them are due to measurement errors and attrition.

[23]Based on the population census data, the proportion of left-behind children in the population of children aged 0—17 is 25 percent and the proportion of migrant children in the population of children aged 0—17 is 13 percent Duan et al. (2013a,b).

[24]The main conclusions are maintained if I run the regression without adjusting for sampling weights. Please refer to Appendix D.

conomic status while migrant and local students are from families with similar socioeconomic status. Figure 1 shows the cognitive test score of various types of students. Ordinary local students who are neither migrant nor left-behind perform better than others. In the sample, 92.3 percent of non-migrant students are enrolled in public schools, while only 85.3 percent of migrant students are enrolled in public schools. One concern is that the variations of proportions of migrant and left-behind peers across classes within schools are created by chance (randomly) (Angrist, 2014). We need check the empirical distributions of the proportion of migrant peers and the proportion of left-behind peers in the data set to make sure there are enough variations. I check two settings of the proportions. First, I check the original distribution of the proportions. Second, I run separately regression of the proportions of migrant and left-behind on the set of school fixed effects, taking the residuals of the regressions and then check the distribution of the residuals. Figure 2 shows the original distribution and Figure 3 shows the distribution of the residualized proportions after controlling for school fixed effects.[25] Both of them support that I have enough variation in these two main independent variables in the regression before and after controlling for school fixed effects. Another concern is that more migrant students may be studying in schools in big cities and more left-behind students may be studying in rural schools. If the concentration is too severe, there may be very little overlapping for migrant and left-behind students in the same class. Then, I will estimate the peer effects of migrant and left-behind students using different classes in different places and it is hard to give any policy implication. To make sure this is not the case, I show the joint distribution of the proportion of migrant and left-behind peers in Figure 4. In this heat map, red area means a higher density. It implies that there are enough overlapping areas for them.

[25]The means of the residualized proportions are about 0 for both of the proportions. The standard deviations are respectively 0.070 and 0.053 for the residualized proportions of migrant and left-behind peers.

3.3 Balance Check

To make sure the randomization works, I conduct some balance checks. The variables of interest are the proportion of migrant peers of some student i in the class, and the proportion of left-behind peers of some student i in the class. For the sample of schools with randomized students assignment, I run regressions of these two proportions of peers on different predetermined characteristics of student i one by one. To begin with, I run regressions without controlling for school fixed effects. In this case, there will be self-selection across schools and classes. Then I run regressions with school fixed effects. In total, I run regressions for thirteen predetermined variables including child's age, sex, whether this child lives at school (boarding), child's hukou type (whether rural hukou 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 their sixth grade (the last year of the primary school) and household economic condition (higher value refers to better economic condition). These variables can capture various aspects of a student's family background and personal characteristics. Specifically, the class ranking in their sixth grade is a proxy of the predetermined ability.

The first and the third column of Table 3 show the results of the regressions without school fixed effects. The second and the fourth column show the results of the regressions with school fixed effects. In general, the results support the true randomization of the students' assignment. Before controlling for school fixed effects, most of the variables are not balanced in different classes with different proportions of migrant and left-behind students. However, after I control for school fixed effects and eliminate the selection across schools, most of the predetermined variables of student i in the table are not significantly correlated with the proportions of left-behind and migrant students in his or her class. Consequently, I am confident that my identification strategy is feasible.[26] There are some other studies using the same data set and employing the same randomization to identify their parameters of interests. They all confirm that the classroom randomization in CEPS does work (Hu, 2018; Gong, Lu, and Song, 2018; Xu, Zhang, and Zhou, 2020).

One problem in the balance check is that there can be a mechanical sampling relation between the leave-one-out peer composition and the student's own characteristics. The basic idea is that when calculating the peer composition, I am excluding student herself. Thus, the peer means can be mechanically different among students in the same school, which is correlated with her personal characteristics. This small bias can diminish when the school size is large. In my case, fortunately, the mean of the number of sampled students in a school is 94 and only 1% of the schools have the number of sampled students to be smaller than 37. Thus, it will not affect the balance check result too much. In addition, I follow the suggestion from Guryan, Kroft, and Notowidigdo (2009) to further control for school level leave-one-out mean of migrant and left-behind students in all the balance check regressions. There is no significant changes. These results are available upon request.

Another concern is that even if the students are randomly assigned to classes, teachers may not be assigned randomly. To investigate whether teachers are assigned randomly, I implement a similar balance check to run regressions of peer compositions on head teachers' personal characteristics. The teacher's characteristics I choose include whether the teacher hold a college degree, the teacher's teaching experience (in years), sex and seniority level. Seniority level is a government evaluation on teachers. A higher level means more teaching experience and better achievement in terms of students' performances. The results are shown in Table 4. It shows the same pattern as in Table 3 that after controlling for school fixed effects, I cannot detect any non-random assignment of head teachers to classes.[27]

[26] I also try several different settings for balance check. First, I run a set of regressions of the proportions of peers on the full set of predetermined variables, rather than one by one. Second, I drop year fixed effects from all the regressions. The results are similar.

[27] Since there are some missing values for control variables in the data, missing values may be correlated with the proportions of migrant and left-behind children. To investigate this issue, I first label all individuals with missing control variables and then run the balance check

4 Results

4.1 Main Results

Table 5 displays results from the main regressions. The dependent variable is the standard cognitive test score, which has a mean of 0.156 and a standard deviation of 0.886. The average number of students in the class is 47.3. In column (1), I do not control for personal and household characteristics. In column (2), I add student *i*'s personal characteristics in the regression. In column (3), I additionally control for student *i*'s household characteristics. In all regressions, I use observations from both waves.[28]

There are several interesting points I can find in the main regression table. In all regressions, both effects of the proportion of migrant peers and the proportion of left-behind peers are negative. In addition, the peer effect of left-behind children is larger in magnitude than the peer effect of migrant children in all specifications. For instance, in column (3), when I add in all the controls, an increase of ten percentage points in the proportion of left-behind peers in the class reduces the test score by 0.106 points, which corresponds to a 0.12 standard deviation decrease. This effect is fairly large compared with results from previous classical studies discussing effects of some other classroom variables on students' performance.[29] The negative effect of the proportion of the migrant peers is only half of the effect of left-behind peers. In the same specification, an increase of ten percentage points in the proportion of the migrant peers in the class reduces the test score by 0.055 points, which corresponds to a 0.062 standard deviation decrease. The magnitude of migrant peers' effect is much smaller than that of left-behind peers.

regression on the missing value indicator. It shows no correlation between the proportions of migrant and left-behind peers and whether a student has some missing information.

[28] The standard errors of all the regressions in this paper are clustered at the school level. There are two reasons for me to choose the school level. First, the CEPS data draws samples in a multi-stage process. They first draw sample counties from all counties in China and then draw sample schools from the sample counties. At last, they draw sample classes from the sample schools and interview all students in the sample classes. This gives a natural structure of the data, and I can cluster at the lowest sampling level, that is, the class level, as suggested in Abadie et al. (2017). However, in some of the regressions, I take advantage of the variations across time, which results in a possible serial correlation. Thus, I cluster at a higher level, that is, the school level, to avoid this problem, as suggested in Angrist and Pischke (2008). I also try to cluster them at the class level, and there is no noticeable change.

[29] For instance, Krueger (1999) used the experiment of Project STAR in the U.S. and found that a smaller class size (a decrease of the number of students in the class from 22—25 to 13—17) can increase a student's standard test score by 0.19—0.28 standard deviations from kindergarten to the third grade.

The pattern is very stable across different regression specifications.[30]

In Table 6, I check the results when I allow the peer effect to be heterogeneous across different migrating-type of student i, by interacting the proportions with the indicator of whether the student i him/herself is an ordinary local student or not. I can find that ordinary local students are more likely to be negatively affected by migrant and left-behind students. Additionally, migrant peers have a smaller negative effect on both ordinary local and non-local students.

4.2 Peer Effects by Duration

In China, classes are fixed during the three years of middle school. In this subsection, I investigate the change of the peer effects over time. To guarantee that the sub-population is consistent, I keep only students who appear in both the first and the second year and then run regressions for the classes and students observed in each wave separately. The results of these regressions can be interpreted as the evolution of the peer effects in terms of the duration of the class for the same population. In the first column of Table 7, I use only observations from the first year, and in the second column, I use only observations from the second year. In the third column, I also use only observations from the second year and additionally control for the test score of the last year, which leads to a value-added model. This column shows the pure second year effect netting out the first year effect. Table 7 shows that in all columns (in both the first and the second year), left-behind peers have larger negative spillovers than migrant peers. The differences in the coefficients are statistically significant when I implement Wald tests.[31] More interestingly, although in the first year the proportion of migrant students and the proportion of left-behind students negatively affects their local classmates, these effects die out in the second year.[32] One year of time cuts the negative effects of left-behind students by more than half and totally erases the negative effects of migrant students on their classmates. When I decompose the effects on

[30]Table A1 in Appendix A shows the corresponding estimates without controlling for school fixed effects. I can detect an upward bias for the peer effects of left-behind students and a downward bias of migrant students if I do not account for the sorting across schools.

[31]Due to the limitation of the space, I do not show the detailed results of Wald tests. They are available upon request.

[32]I can derive a standard error for the difference between the coefficients in the two regressions in the first and second years using a bootstrap process. It shows that both of the differences are statistically significant from zero.

ordinary local students and non-ordinary local students in Table 8, the mitigation of the effects across time holds for both of them. It is likely that as long as students get used to lives in the new places they go to, they will not negatively affect their classmates. This may alleviate the concern from local parents in developed areas that migrant students from under-developed areas can negatively affect their children since the negative effects are totally eliminated in their second year of study. I will formally investigate how migrant and left-behind students in the class can affect the class environment and classmates' relationships in Section 5.2. However, for left-behind students, even though their negative effects are reduced in the second year, those effects are still significant economically and statistically. Living without parents and studying without careful supervision seem to have a long-lasting harmful effect not only on themselves (as the previous literature has claimed), but also on their classmates.[33]

4.3 Implications of the Results

In general, I have four main conclusions. First, the proportion of left-behind students in the class can negatively affect the test score of a student. Second, the proportion of migrant students in the class has only small effects on the test score of a student. Third, the negative peer effect on ordinary local students is larger than the effect on non-local students. Fourth, in the second year, the negative peer effects of migrant students disappear and the negative peer effects of left-behind students are reduced.

The results reveal important policy implications to us. In some cases when local governments in developed areas (usually cities in eastern provinces) relax their policy restrictions for the migrant children to enter public schools, local parents launch protests and claim that the inflow of children from developing areas (usually rural areas) will harm local children. In my regressions however, I do not find much evidence supporting this claim. Migrant peers only

[33] An alternative explanation for the shrinkage of the negative peer effects in the second year is that the "bad apples" in the class drop out, which creates a better class environment. This seems not to be the case in my setting considering the drop out rate is minimal in the sample. In the CEPS data set, the attrition rate due to student drop outs is 1.18 percent. I check it in detail in Appendix B.

moderately affect local students. Even if there is some negative effect at first, it will disappear or even turn to be positive in the second year. Meanwhile, left-behind children seem to have a larger and long-lasting damage on their classmates and government should pay more attention to help them.

Furthermore, it seems that the relaxation of the restrictive enrollment policy on migrant students in developed areas cannot only benefit migrant students by attracting more parents to migrate with their children, but also reduce the overall negative spillovers on these students' classmates. Using a simple back of envelope calculation, we can evaluate the social gain of this policy very roughly. If we can move one left-behind student to migrate with their parents, there will be 0.0258 standard deviation gain for each of his or her classmate and 1.22 standard deviation gain for the whole class in the first year. In the second year, there will be 0.0244 standard deviation gain for each of the classmate and 1.15 standard deviation gain for the whole class.[34] Huang (2020) constructs a spatial equilibrium model and investigates the human capital gains in details.

However, there are selections on children's migration choices which could lead to typical external validity concerns for this policy implication. Left-behind students may come from more disadvantaged families and have lower abilities. Larger negative spillovers of left-behind students then could result from negative selection but not the consequence of being left-behind. I will discuss it in detail in Section 5.3.

5 Mechanism

In this section, I will consider different mechanisms through which migrant students and left-behind students can affect their classmates. I will try to explain why left-behind students have persistent negative effects on their classmates and why the negative effects of migrant students

[34] The average class size in the data is 47.3. The average proportion of migrant peers and average proportion of left-behind peers in the data are respectively 0.221 and 0.156. When we hold the class size constant, the change of the proportion of migrants and left-behind students are calculated as $0.156 - \frac{47.3 \times 0.156 - 1}{47.3} \approx 0.0211$. Multiplying it by the difference between the estimates of the negative spillovers in Table 7 (normalized in standard deviation unit), we can derive the results.

disappear in the second year. I will also argue that the selection in migration is only one part of the reason why migrant and left-behind students have negative effects on their classmates but not the whole story, which is important to the external validity and policy implication.

5.1 Students' Misbehavior

The first set of factors I investigate is students' misbehavior. As some previous studies have found (Case and Katz, 1991; Gaviria and Raphael, 2001; Li, Zang, and An, 2013), misbehavior of a student can "contaminate" his or her classmates. It is likely that students will mimic the behavior of their friends who smoke, fight or drop out of school.

Due to the change in survey questions across waves, I run regressions separately for observations in 2013 and 2014. In the first wave, the survey asks students whether they are often late for school and whether they often skip classes. In the second wave, the survey asks students whether they are often involved in fights, whether they often bully other people, whether they often skip classes, whether they often cheat in exams, whether they often smoke and whether they often go to video gaming bars. In Table 9 and Table 10, for each of the indicator variable created by the answer of these questions, I run the regression of the misbehaving indicator of a student on the proportion of migrant peers in his or her class, the proportion of left-behind peers in his or her class, the indicator of whether the student is a migrant, the indicator of whether the student is a left-behind and some other controls.[35] Then I can check for two effects: first, the causal peer effects of migrant classmates and left-behind classmates on student's misbehavior; second, the correlation between the student's migrating type (whether he or she is a migrant/left-behind/local) and the student's misbehavior.

Table 9 shows the results of the first wave. It demonstrates that a higher proportion of left-behind classmates and a higher proportion of migrant classmates can result in higher probability of a student to be often late for school and often skip classes. However, only one of the estimates

[35] In the regressions from previous sections, the indicator of whether the student is a migrant and the indicator of whether the student is a left-behind are also controlled within the set of personal controls. Here, I explicitly show their coefficients in the table.

is statistically significant.

Table 10 displays the results of the second wave. In this wave, I have more variables available. For some of them, I can find statistically significant positive peer effects on misbehavior. For instance, an increase of ten percentage points in the proportion of left-behind peers in the class can lead to 2.27 percentage points increase in the probability for a student to be often involved in fights. The average probability of the student to be involved in fights is 6.47 percent in the data, which means the 2.27 percentage points increase is equivalent to a 35.1 percent increase relative to the average rate. In addition, being a left-behind student is correlated with a 4.2 percentage points (64.9%) increase in the probability of being often involved in fights. Combining these two facts, I can infer that left-behind students may often get into trouble with others and trigger more fights in their classes with their classmates. The peer effects also exist for the indicators of cheating in exams and going to video gaming bars. An increase of ten percentage points in the proportion of migrant peers and left-behind peers will respectively lead to 2.69 percentage points (33.5%) and 1.82 percentage points (22.7%) increase in the probability of the student to often cheat in exams. An increase of ten percentage points in the proportion of migrant peers and left-behind peers will respectively lead to increases of 1.24 percentage points (26.8%) and 1.35 percentage points (29.2%) in the probability of the student to often go to video gaming bars. Moreover, left-behind students are 2.14 percentage points (90.7%) more likely to often smoke and migrant students are 4.1 percentage points (88.7%) more likely to often go to video gaming bars (although these are just correlations). In the last two columns of the table, I combine the six measures of misbehavior together into one index and run the regressions. First, I use a simple mean of the previous six variables to measure the mean score of a student's misbehavior. Second, I use the first principal component of the previous six variables as a new combined index. The results show that generally, the increase of the proportion of migrant and left-behind peers in the class can increase a students' misbehavior, and the effect is more severe from the left-behind peers.[36] All the estimates suggest that even in the second year, more left-behind classmates can still lead to more misbehavior of a student. Aligning with the story, in Appendix C, I also find that students with the lowest abilities (usually students who are most likely to conduct misbehavior) are affected the most by their left-behind peers.

An anecdotal story claims that the misbehavior of left-behind students is due to the lack of the supervision of their parents. To test this story, I run some more regressions to discover the correlation between parents' care and being left behind. The dependent variables are whether parents care much about the student's exam, whether parents care about the student's general school performance, whether parents pay attention to the time the student spends on the Internet, whether parents pay attention to the time the student spends on TV, whether the relation between the student and his or her mother is good and whether the relation between the student and his or her father is good. These questions are answered by students. Table Table 11 and 12 reveal an obvious negative correlation between being left behind and parents' supervision in both the first and the second year, which implies a persistent damage of the children-parents relationship for left-behind students.. Parents of left-behind students care less about their children's exams, school performances, time spent on the Internet and time spent on TV and the relations between parents and left-behind children are worse.[37] The last two columns of Table 11 and 12 are similar to the last two columns of Table 10, where I use two combined indexes as the dependent variables. The negative correlation between being left-behind and the lack of parents' care is significant.

I then run a set of regressions of student's test score on both the proportion of migrant and left-behind peers in the class and average misbehavior rates of their classmates. Table 13 shows the results. Column (1) is the baseline when I do not add in average misbehavior rates. I can

[36] Although some of the coefficients on the index measures are not statistically significant, they are at the margin of significance.

[37] For example, in the first year, parents of left-behind students are 11.3 percentage points (20.4%) less likely to care much about their children's exams, 6.92 percentage points (15.4%) less likely to care much about their children's school performances, 3.94 percentage points (5.67%) less likely to care much about their children's time spent on the Internet and 5.06 percentage points (10.1%) less likely to care much about their children's time spent on TV. Left-behind children are 5.27 percentage points (6.86%) and 6.72 percentage points (10.1%) less likely to have a good relationship with their mothers and fathers.

find that the average misbehavior rate in the class is negatively correlated with the test score of a student. In addition, the point estimates are reduced when I control the average level of misbehavior in the class and some of the peer effects of the proportion of migrant and left-behind peers are absorbed.[38]

Generally, the misbehavior of students is an important channel for migrant and left-behind students to negatively affect their classmates, especially for left-behind students. The misbehavior of left-behind students may result from the absence of their parents. Furthermore, the detrimental effect of left-behind students on their classmates' misbehavior and the damage of the children-parents relationship of left-behind students persist across time, which may explain the persistence of the negative peer effect of left-behind children on the test score of their classmates. The government should try to take care of them and give them proper supervision on their behaviors in the absence of their parents.

5.2 Classroom Environment

The second channel I inspect is the change of class environment resulting from the appearance of migrant students and left-behind students. Students are asked questions about whether their classmates are friendly to them and whether the learning atmosphere in the class is good.[39] I run regressions of these indicators of class environment on the proportion of migrant peers and left-behind peers to check the peer effects on class environment. To test the hypothesis I made in Section 4.2 about the decay of the peer effects across time, I keep students appearing in both waves and run the regressions separately for the first wave and the second wave.

The results are shown in Table 14 and 15. In Table 14, regressions are implemented on the sample from the first year. In Table 15, regressions are implemented on the sample from the second year. As in the last section, I also construct two combined indexes to reflect the overall

[38] As students' misbehaviors are post-determined endogenous variables, the coefficients of these regressions do not have causal interpretations. Thus, I can only get some qualitative conclusions.

[39] They rate each question from 1 to 4 based on the magnitude of agreement, with 1 as totally disagree, 2 as disagree, 3 as agree and 4 as totally agree. I combine 1 and 2 as disagree (valued 0); 3 and 4 as agree (valued 1).

classroom environment and use them as the dependent variables in the third (average index) and the fourth (first principal component) columns. Some conclusions can be drawn. First, the higher proportion of left-behind peers and migrant peers in the class induce both a group of less friendly classmates and a worse learning environment. Second, the damage caused by left-behind students is larger than that caused by migrant students. The differences are statistically significant in Wald tests. Third, the negative peer effects on class environment decline in the second wave in 2014. For the peer effects of migrant students on classroom environment, the estimates become statistically insignificant. These three conclusions are very similar to the conclusions I have in main regressions when the dependent variables are students' standard test scores. Tables 16 and 17 show the results when I add average class environment variables to the main regressions in the first and the second year separately.[40] The average class environment variables are calculated as the means of the indicators of class environment for all of student i's classmates. Column (1) of both tables are the baselines when I do not add in average class environment rates. It is clear that in both years, the classroom environment is positively correlated with students' test score and once I control for the average class environment, the original peer effects on students' test scores are reduced.

Thus, it is likely that left-behind students and migrant students can harm the classroom environment and lead to a lower academic achievement of their classmates. However, as time goes by, they can get along with their classmates well and the negative effects will be relieved. For migrants, in the second year, I do not find significant negative effects from them on the classroom environment. This could be the reason why migrant students have no negative effects on their classmates' test scores in the second year. My findings support the assimilation of the migrant students in their new classes. To further test this mechanism, I run a regression additionally controlling for the proportion of migrant students who have migrated for more than

[40] As class environments are post-determined endogenous variables, the coefficients of these regressions do not have causal interpretations. Thus, I can only get some qualitative conclusions.

five years. Table 18 shows that these is no negative spillovers from these long-term migrant students. All the negative peer effects come from new migrant students in the first year.

5.3 Family Background

One potential policy implication is that I can reduce the overall negative spillover by relaxing the enrollment restriction on migrant students and encouraging parents to take their children with them when they migrate. However, the peer effects may result from the selection on migration. If the differences in peer effects between left-behind and migrant students are totally attributed to the fact that left-behind students have lower "ability" and they are from families with lower socioeconomic status, but not from the consequences of being left behind, then the external validity of the estimates of the peer effects could be limited. Once we change the policy, the peer effects will also change according to the change of the composition of migrants. If the selection is the whole story, then policy recommendation of relaxing the public school enrollment restriction on migrant students to reduce the overall negative spillover will not be cogent. In this section, I explore whether this is true.

In the main regression, I run the test score of a student on the proportion of migrant and left-behind peers in his or her class. To investigate the effect resulting from peers' pre-determined family background, I additionally control for average family background of a student's classmates. The control variables include average socioeconomic condition of the classmates, average father's education year of the classmates and average mother's education year of the classmates. Since the assignment of students into classes is random, these averaged variables about the family background of the classmates should also be exogenous. If I detect zeros of the coefficients of the proportion of migrant peers and the proportion of left-behind peers, it means that the family background is likely to be the only channel for the peer effects.

Results are exhibited in Table 19. Column (1) displays the result from the main regression as a reference (same as Column (3) in Table 5.). I do find evidence that after controlling for these pre-determined family background, point estimates of peer effects reduce, though they are still negative and more than half of the negative spillovers cannot be explained by the inclusion of pre-determined factors. The results reveal that migrant and left-behind students affect their classmates due to the fact that they migrate or they are left behind, rather than just because they are from disadvantaged families compared with others. Meanwhile, in all specifications, when I net out pre-determined family background, the negative peer effects of left-behind peers are still more significant than the negative peer effects of migrant peers, both economically and statistically.[41]

Another way to net out the pre-determined characteristics from the peer effects is to run the main regression and additionally control for the average test scores of the migrant peers and the left-behind peers in the previous period (the first period). The average test scores of the migrant peers and the left-behind peers can be used as a proxy of the average time-invariant "ability" and family characteristics of migrant and left-behind peers. It should absorb the effects of factors determined before the current period (the second period). Results are shown in Table 20. In the first column, I do not control for the average scores of the migrant peers and the left-behind peers in 2013, which can be considered as a baseline. Comparing the second column with the first column, I can see that there is reduction in the estimate of the peer effects of left-behind students. However, I still detect a significant negative spillover, which means that pre-determined factors must not be the whole story.

Combined with the detection of other channels in previous sections, the results can be considered as a relief of the typical external validity criticism. I find that although selection is one part of the reason, it is not the only reason for the negative spillovers of left-behind students. Relaxing the enrollment restriction for migrants and encouraging migrant parents to take their children with them can reduce the overall negative spillover.

[41] I also run the regressions on the sample only from the first year and only from the second year separately. The basic conclusions are similar. In addition, I run the regression only on family background variables but not proportions of migrant and left-behind peers. I can find that the direct effect of classmates' average family background is much smaller than the effect of the proportion of migrant and left-behind peers. The tables are available upon request.

6 Robustness Checks

I change some specifications to check the robustness of my results. Three regressions are run in each specification: the regression on both years; the regression on the sample from the first year and the regression on the sample from the second year.

In Table 21, I change the student's performance measurement from cognitive test scores to school-level standardized Chinese, Math and English test scores, which are used in Hu (2018) and Wang, Cheng, and Smyth (2018). The first column of each measurement is regression with observations from both years, which corresponds to column (3) in Table 5. The second column of each measurement is regression with only observations from the first year, which corresponds to column (1) in Table 7. The third column of each measurement is regression with only observations from the second year, which corresponds to column (2) in Table 7 (similar for other tables in this section). Though the point estimates may be biased as I mentioned, my main conclusions still hold qualitatively. Migrant students will negatively affect their classmates' Chinese scores but will not affect their classmates' Math and English scores significantly. However, left-behind students can harm their classmates' on all of the three subjects and the magnitudes are much larger. Moreover, I can also detect reductions in point estimates in the second year. In Table 22, I change the independent variables to be the proportion of rural migrant peers and the proportion of rural left-behind peers in the class. The only difference in the definition is that now I only consider migrant students and left-behind students with rural Hukou. The results are similar to the main regression table.[42] I also change the definition of left-behind children in Table 23. In the main setting, I define left-behind children as children with at least one of their parents not living with them. In this table, I change it to children with both of their parents absent (still excluding cases of divorces and parents' deaths). The results show that the negative effects of left-behind peers become larger, which makes sense because usually these children

[42]In fact, I run all the regressions in previous sections with the traditional school-level Chinese, Math and English scores as the dependent variable. All the qualitative conclusions hold firmly in all specifications. These results are available upon request.

are in more disadvantaged positions than children with at least one parent at home.

In Angrist (2014), he raises questions about the interpretation of the peer effect coefficient in traditional linear-in-mean model. He claims that the estimate of peer effect is equivalent to the difference (or ratio) between the OLS estimation of y on individual covariate x and 2SLS estimation of y on individual covariate x using group dummies z as instruments. However, the discrepancy between them can be attributed to not only peer effects. He suggests to *"make a clear separation between the subject of a peer effects investigation and the peers who provide the mechanism for causal effects on these subjects"*. Thus, in my case, I run the regressions only on ordinary local students who are neither migrant nor left-behind students, to test whether the results are robust or not.[43] Table 24 shows that all the point estimations are very similar to the results in Table 5 and 7. Specifically, Angrist (2014) claims that one of the possible reasons for the discrepancy is the measurement error on x. I have two responses for this. First, Feld and Zölitz (2017) proves that this type of measurement error will only attenuate the peer effect estimation towards zero rather than amplifying it when the assignment of students in groups is random (as in my case). Second, I follow the suggestion from Carrell, Hoekstra, and Kuka (2018) and Feld and Zölitz (2017) to implement some simulation and find that by adding measurement error in the sample, the point estimates are attenuated rather than amplified, which rules out Angrist's concern.[44]

I implement some further robustness checks in Appendix D. Generally, all main conclusions hold in different specifications.

7 Conclusion

In this study, I investigate the peer effects of migrant students and left-behind students on their classmates, employing the random assignment of students into classes in middle schools in

[43] The regressions are similar to the ones in Carrell, Hoekstra, and Kuka (2018).

[44] The details of the simulation practice are shown in Appendix D.

China. This is one of the first studies using a nationally representative panel data with classroom random assignment to attack the difficulties in identifying peer effects.

Results show that more migrant peers and more left-behind peers in the class can reduce the test scores of a student and the detrimental effect of left-behind peers is much larger than that of migrant peers. I also show that as students study together for a longer time, the classroom environment will become better and the negative effect of migrant peers will be totally erased. The negative effects of left-behind peers are halved in the second year but still exist.

Left-behind students have large and more persistent negative effects on their classmates due to the long-lasting "contamination" of misbehavior and the lack of their parents' supervision. While migrant students are not "bad apples" among their classmates. One of the reasons why they may negatively affect their classmates in the first year of study is because they need time to adapt to the environment. The government should help them to integrate in their classes and schools. In addition, left-behind children seem to have long-lasting negative effects on their classmates, and the government should pay more attention to provide them with proper supervision and help.

A potential policy implication from this paper is that the government might reduce the negative spillovers by relaxing enrollment restrictions for migrant students and encouraging parents to take their children with them when they migrate. One concern of this policy is that left-behind and migrant families are self-selected and the point estimates in this study may not be extrapolated. I alleviate this problem by claiming that pre-determined family background and self-selection is not the only reason of the negative spillover with some empirical evidence. Thus, encouraging left-behind students to migrate with their parents still at least has some positive effect on the overall spillovers. In general, this is also a new evidence supporting the elimination of the Hukou system in China, from a perspective of children's human capital accumulation. Nevertheless, I cannot fully solve the external validity problem and the estimates in this paper still cannot be directly used in any formal counterfactual calculation. Huang (2020) gives a more detailed discussion about this.

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Table 1: Summary Statistics of Schools With/Without Random Assignment

Variable	With Random	Without Random	Differences
Urban School	0.632	0.615	0.0169
	(0.484)	(0.490)	(0.0718)
Public School	0.929	0.938	-0.00943
	(0.258)	(0.242)	(0.0374)
School Ranking	3.819	3.969	-0.149
	(0.825)	(0.0.925)	(0.127)
Proportion of Migrant Students	0.219	0.179	0.0405
	(0.218)	(0.190)	(0.0310)
Proportion of Left-behind Students	0.190	0.143	0.0467**
	(0.167)	(0.120)	(0.0229)

Notes: In the first column, I show the mean values and the standard deviations of different variables for schools with random assignment of students. In the second column, I show the mean values and the standard deviations of different variables for schools without random assignment of students, which are dropped in the regression analysis. In the third column, I calculate the differences of the mean values for schools with/without random assignment and their corresponding standard errors. T-tests are also implemented in the third column.

Table 2: Summary Statistics

Variable	Migrant	Left-Behind	Local
Student Gender(=1 if boy)	0.524	0.552	0.499
	(0.500)	(0.497)	(0.500)
Student Age	12.985	12.985	12.934
	(0.864)	(0.939)	(0.829)
Student Hukou Type(=1 if rural)	0.606	0.620	0.397
	(0.489)	(0.486)	(0.489)
Father Education Years	10.290	9.586	11.156
	(3.104)	(2.909)	(3.383)
Mother Education Years	9.477	8.562	10.616
	(3.343)	(3.704)	(3.659)
Socioeconomic Condition	2.891	2.700	2.878
	(0.542)	(0.666)	(0.583)
Standardized Test Scores	0.129	-0.0770	0.240
	(0.864)	(0.891)	(0.870)

Notes: The summary statistics are calculated on the final sample using all school 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.

Table 3: Balance Check

	Proportion of Migrants		Proportion of Left-Behinds	
	Without School FE	With School FE	Without School FE	With School FE
Age	-0.0147	0.00142	0.0520***	0.00278
	(0.0115)	(0.00114)	(0.0135)	(0.00342)
Sex	0.0128**	0.00187	0.00874	0.000298
	(0.00509)	(0.00140)	(0.00677)	(0.00132)
Board	-0.0574	-0.0109	0.126***	0.00106
	(0.0360)	(0.00815)	(0.0374)	(0.00296)
Hukou Type	-0.0288*	-0.000781	0.0851***	0.00630
	(0.0148)	(0.00354)	(0.0198)	(0.00717)
Whether Migrant Student	0.258***	0.0168	-0.0659***	-0.00530
	(0.0507)	(0.0196)	(0.0183)	(0.00393)
Whether Left-behind Student	-0.0494***	-0.00384	-0.140***	-0.00226
	(0.0130)	(0.00289)	(0.0204)	(0.00659)
Only Child	-0.00381	0.00185	0.121***	0.00456
	(0.0264)	(0.00171)	(0.0204)	(0.00527)
Father Education years	0.00263	-0.000551	-0.0149***	-0.00105
	(0.00303)	(0.000645)	(0.00288)	(0.000996)
Mother Education Years	0.00300	-0.000307	-0.0162***	-0.000861
	(0.00281)	(0.000533)	(0.00228)	(0.000973)
Whether Parents Have Conflicts	0.00336	-0.000383	0.0261**	-0.000126
	(0.0114)	(0.00156)	(0.0107)	(0.00361)
Sixth Year Ranking	-0.000633**	0.0000663	0.000929***	0.0000361
	(0.000307)	(0.0000700)	(0.000350)	(0.000108)
Household Economic Condition 2	0.0251***	0.00425*	-0.00107	-0.00234
	(0.00823)	(0.00222)	(0.00978)	(0.00463)
Household Economic Condition 3	0.0652***	0.00491*	-0.103***	-0.0121
	(0.0165)	(0.00258)	(0.0167)	(0.0107)
Household Economic Condition 4	0.0650***	0.00502	-0.144***	-0.0106
	(0.0225)	(0.00329)	(0.0235)	(0.00956)
Household Economic Condition 5	0.0536	0.00514	-0.137***	-0.00997
	(0.0326)	(0.00894)	(0.0322)	(0.0104)
School Fixed Effect	NO	YES	NO	YES
Year Fixed Effect	YES	YES	YES	YES

Notes: In the first two columns, I run regressions of proportion of migrant children on different variables with/without controlling for school fixed effects. In the third and the fourth columns, I run regressions of 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 correlation between the independent variable and the composition of the children in the class. All the standard errors are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 4: Balance Check for Teachers

	Proportion of Migrants		Proportion of Left-Behinds	
	Without School FE	With School FE	Without School FE	With School FE
College	0.0353	0.0126	-0.0179	0.00257
	(0.0260)	(0.0169)	(0.0339)	(0.0164)
Teaching Experience	0.00193	0.00199	-0.00707***	-0.00123
	(0.00182)	(0.00144)	(0.00173)	(0.00109)
Sex	-0.0166	0.00528	0.0746**	0.0233
	(0.0252)	(0.0102)	(0.0362)	(0.0155)
Teacher Level 1	-0.132***	0.000399	-0.0679	-0.00228
	(0.0493)	(0.0287)	(0.0856)	(0.0876)
Teacher Level 2	0.0240	0.0652	-0.149***	-0.0201
	(0.0450)	(0.0400)	(0.0520)	(0.0443)
Teacher Level 3	0.0399	0.0499	-0.213***	-0.0346
	(0.0477)	(0.00329)	(0.0418)	(0.0427)
Teacher Level 4	-0.0491	0.0630	-0.224***	-0.0561
	(0.0569)	(0.0535)	(0.0485)	(0.0422)
School Fixed Effect	NO	YES	NO	YES
Year Fixed Effect	YES	YES	YES	YES

Notes: In the first two columns, I run regressions of proportion of migrant children on different variables with/without controlling for school fixed effects. In the third and the fourth columns, I run regressions of 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 correlation between the independent variable and the composition of the children in the class. All the standard errors are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 5: Peer Effects of Migrant Children and Left-Behind Children on Standard Cognitive Scores

	(1)	(2)	(3)
Proportion of Migrant Peers	-0.605*	-0.567*	-0.545*
	(0.319)	(0.297)	(0.286)
Proportion of Left-Behind Peers	-1.198**	-1.124**	-1.061**
	(0.514)	(0.448)	(0.432)
School FE	YES	YES	YES
Year Dummy	YES	YES	YES
Personal Controls	NO	YES	YES
Household Controls	NO	NO	YES
Observations	11,519	11,519	11,519
R-squared	0.292	0.310	0.314

Notes: The dependent variable is the standard test score for all regressions. For column (1), I do not control for personal characteristics and household characteristics. For column (2), I do not control for household characteristics. For column (3), I control for all sets of variables. The set of personal controls includes student's own 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 and whether he or she lives at school. The set of household controls includes household economic condition, mother's education and father's education. All the standard errors are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 6: Peer Effects of Migrant Children and Left-Behind Children by Migrating Types

	(1)	(2)	(3)
Proportion of Migrant Peers	-0.561*	-0.425	-0.409
	(0.315)	(0.267)	(0.260)
Proportion of Left-Behind Peers	-1.313**	-1.059**	-1.017**
	(0.526)	(0.434)	(0.418)
Proportion of Migrant Peers # Local	-0.103	-0.346**	-0.330**
	(0.129)	(0.148)	(0.145)
Proportion of Left-Behind Peers # Local	0.162**	-0.0958	-0.0656
	(0.0708)	(0.109)	(0.110)
School FE	YES	YES	YES
Year Dummy	YES	YES	YES
Personal Controls	NO	YES	YES
Household Controls	NO	NO	YES
Observations	11,519	11,519	11,519
R-squared	0.292	0.311	0.315

Notes: The dependent variable is the standard test score for all regressions. For column (1), I do not control for personal characteristics and household characteristics. For column (2), I do not control for household characteristics. For column (3), I control for all sets of variables. The set of personal controls includes student's own 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 and whether he or she lives at school. The set of household controls includes household economic condition, mother's education and father's education. All the standard errors are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 7: Peer Effects of Migrant Children and Left-Behind Children by Duration

	(1) First Year	(2) Second Year	(3) Second Year
Proportion of Migrant Peers	-0.976**	-0.0265	0.238
	(0.371)	(0.328)	(0.262)
Proportion of Left-Behind Peers	-2.062**	-1.050***	-0.687***
	(0.792)	(0.311)	(0.235)
Test Score in 2013			0.463***
			(0.0297)
School-Grade FE	YES	YES	YES
Personal Controls	YES	YES	YES
Household Controls	YES	YES	YES
Observations	4,072	4,072	4,072
R-squared	0.359	0.335	0.488

Notes: The dependent variable is the standard test score for all regressions. I keep only the observations appearing in both waves to make the regressions comparable in terms of the sample. For column (1), I use data from the first year. For columns (2)—(3), I use the data of the same group of people from the second year. The set of personal controls includes student's own 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 and whether he or she lives at school. The set of household controls includes household economic condition, mother's education and father's education. All the standard errors are clustered at the school level. I only include students and classes observed in both of the waves. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 8: Peer Effects by Migrating Types and Duration

	(1) First Year	(2) Second Year	(3) Second Year
Proportion of Migrant Peers	-0.866**	0.0857	0.253
	(0.337)	(0.361)	(0.282)
Proportion of Left-Behind Peers	-2.031**	-0.672	-0.316
	(0.775)	(0.406)	(0.348)
Proportion of Migrant Peers # Local	-0.262	-0.391*	-0.141
	(0.177)	(0.221)	(0.140)
Proportion of Left-Behind Peers # Local	-0.0309	-0.548*	-0.528*
	(0.260)	(0.312)	(0.289)
Test Score in 2013			0.462***
			(0.0294)
School FE	YES	YES	YES
Year Dummy	YES	YES	YES
Personal Controls	YES	YES	YES
Household Controls	YES	YES	YES
Observations	4,072	4,072	4,072
R-squared	0.360	0.337	0.489

Notes: The dependent variable is the standard test score for all regressions. I keep only the observations appearing in both waves to make the regressions comparable in terms of the sample. For column (1), I use data from the first year. For columns (2)—(3), I use the data of the same group of people from the second year. The set of personal controls includes student's own 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 and whether he or she lives at school. The set of household controls includes household economic condition, mother's education and father's education. All the standard errors are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 9: Students' Misbehaviors and The Peer Effects: First Year

	Often Late	Often Skip Class
Proportion of Migrant Peers	0.0298	0.0408
	(0.0345)	(0.0302)
Proportion of Left-Behind Peers	0.141*	0.0833
	(0.0764)	(0.0670)
Whether Is a Migrant	-0.0117	-0.00773
	(0.00708)	(0.00968)
Whether Is a Left-Behind	-0.000354	-0.00574
	(0.0130)	(0.00932)
School FE	YES	YES
Personal Controls	YES	YES
Household Controls	YES	YES
Observations	4,387	4,387
R-squared	0.036	0.042

Notes: The dependent variables are respectively the indicators of whether the student is often late for school and whether the student often skips classes. The set of personal controls includes student's own 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 and whether he or she lives at school. The set of household controls includes household economic condition, mother's education and father's education. All the standard errors are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 10: Students' Misbehaviors and the Peer Effects: Second Year

	Often Fight	Often Bully	Often Skip Class	Often Cheat	Often Smoke	Often Gaming	Average Index	First Principal Component
Proportion of Migrant Peers	-0.0899	0.0582	-0.0364	0.269***	0.0424	0.124***	0.0614*	0.620
	(0.0996)	(0.0620)	(0.0225)	(0.0530)	(0.0356)	(0.0435)	(0.0364)	(0.445)
Proportion of Left-Behind Peers	0.227***	-0.00447	-0.00130	0.182***	0.0126	0.135**	0.0918**	0.869
	(0.0469)	(0.0508)	(0.0433)	(0.0599)	(0.0519)	(0.0607)	(0.0424)	(0.587)
Whether Is a Migrant	0.00537	-0.00324	0.00203	-0.00661	0.0135	0.0408***	0.00864	0.118
	(0.0181)	(0.0116)	(0.0118)	(0.0196)	(0.0120)	(0.0147)	(0.00888)	(0.119)
Whether Is a Left-Behind	0.0420*	-0.000282	-0.00435	0.0197	0.0214**	0.0151	0.0156*	0.170
	(0.0211)	(0.0109)	(0.00807)	(0.0271)	(0.00932)	(0.0158)	(0.00836)	(0.102)
School FE	YES	YES	YES	YES	YES	YES	YES	YES
Personal Controls	YES	YES	YES	YES	YES	YES	YES	YES
Household Controls	YES	YES	YES	YES	YES	YES	YES	YES
Observations	4,088	4,088	4,088	4,088	4,088	4,088	4,088	4,088
R-squared	0.060	0.023	0.071	0.082	0.042	0.074	0.085	0.076

Notes: The dependent variables of the first six columns are respectively the indicators of whether the student is often involved in fights at school, whether the student often bullies his or her classmates, whether the student often skips classes, whether the student often cheats in exams, whether the student often smokes and whether the student often goes to video gaming bars. In the seventh column, I use the mean of the first six variables as an average index of students' misbehavior to be the dependent variable. In the last column, I use the first principal component of the first six variables to be the dependent variable. The set of personal controls includes student's own 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 and whether he or she lives at school. The set of household controls includes household economic condition, mother's education and father's education. All the standard errors are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 11: Relation With Parents: First Year

	On Exam	On School Performance	On Internet	On TV	Relation with Mother	Relation with Father	Average Index	First Principal Component
Whether Is a Migrant	0.0290	0.00102	0.0370	-0.00586	0.0231	-0.00485	0.0132	0.0716
	(0.0399)	(0.0378)	(0.0344)	(0.0380)	(0.0307)	(0.0438)	(0.0283)	(0.143)
Whether Is a Left-Behind	-0.113***	-0.0692**	-0.0394	-0.0506	-0.0527***	-0.0672**	-0.0654***	-0.330***
	(0.0308)	(0.0310)	(0.0291)	(0.0308)	(0.0195)	(0.0277)	(0.0129)	(0.0688)
School FE	YES	YES	YES	YES	YES	YES	YES	YES
Year Dummy	YES	YES	YES	YES	YES	YES	YES	YES
Personal Controls	YES	YES	YES	YES	YES	YES	YES	YES
Household Controls	YES	YES	YES	YES	YES	YES	YES	YES
Observations	3,944	3,944	3,944	3,944	3,944	3,944	3,944	3,944
R-squared	0.059	0.050	0.061	0.036	0.088	0.083	0.099	0.092

Notes: All the regression are run on the sample of the first wave (2013). The dependent variables of the first six columns are respectively the indicators of whether parents care much about student's exam, whether parents care about the student's general school performance, whether parents pay attention to the time the student spends on the Internet, whether parents pay attention to the time the student spends on TV, whether the relation between the student and his or her mother is good and whether the relation between the student and his or her father is good. In the seventh column, I use the mean of the first six variables as an average index of students' relations with their parents to be the dependent variable. In the last column, I use the first principal component of the first six variables to be the dependent variable. The set of personal controls includes student's own 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 and whether he or she lives at school. The set of household controls includes household economic condition, mother's education and father's education. All the standard errors are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 12: Relation With Parents: Second Year

	On Exam	On School Performance	On Internet	On TV	Relation with Mother	Relation with Father	Average Index	First Principal Component
Whether Is a Migrant	-0.00575	-0.0871***	0.0116	0.0512	-0.0228	-0.0245	-0.0129	-0.0532
	(0.0299)	(0.0291)	(0.0346)	(0.0385)	(0.0286)	(0.0304)	(0.0191)	(0.0985)
Whether Is a Left-Behind	-0.0239	-0.0448**	-0.0297	-0.00932	-0.0770***	-0.119***	-0.0506***	-0.211**
	(0.0413)	(0.0207)	(0.0337)	(0.0238)	(0.0271)	(0.0301)	(0.0170)	(0.0896)
School FE	YES	YES	YES	YES	YES	YES	YES	YES
Year Dummy	YES	YES	YES	YES	YES	YES	YES	YES
Personal Controls	YES	YES	YES	YES	YES	YES	YES	YES
Household Controls	YES	YES	YES	YES	YES	YES	YES	YES
Observations	3,944	3,944	3,944	3,944	3,944	3,944	3,944	3,944
R-squared	0.080	0.071	0.062	0.040	0.079	0.079	0.108	0.099

Notes: All the regression are run on the sample of the second wave (2014). The dependent variables of the first six columns are respectively the indicators of whether parents care much about student's exam, whether parents care about the student's general school performance, whether parents pay attention to the time the student spends on the Internet, whether parents pay attention to the time the student spends on TV, whether the relation between the student and his or her mother is good and whether the relation between the student and his or her father is good. In the seventh column, I use the mean of the first six variables as an average index of students' relations with their parents to be the dependent variable. In the last column, I use the first principal component of the first six variables to be the dependent variable. The set of personal controls includes student's own 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 and whether he or she lives at school. The set of household controls includes household economic condition, mother's education and father's education. All the standard errors are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 13: Adding Students' Misbehaviors in the Main Regression: Second Year

	(1)	(2)	(3)	(4)
Proportion of Migrant Peers	-0.0193	0.201	0.160	0.0928
	(0.322)	(0.253)	(0.259)	(0.357)
Proportion of Left-Behind Peers	-1.057***	-0.514**	-0.583**	-0.603**
	(0.319)	(0.234)	(0.247)	(0.268)
Average of Classmates Misbehavior Average Index		-3.822**		
		(1.652)		
Average of Classmates Misbehavior FPC Index			-0.291**	
			(0.141)	
Average of Classmates Often Fight				-1.393**
				(0.664)
Average of Classmates Often Bully				-2.739**
				(1.333)
Average of Classmates Often Skip Class				-1.055*
				(0.585)
Average of Classmates Often Cheat				0.278
				(0.468)
Average of Classmates Often Smoke				-0.218
				(2.301)
Average of Classmates Often Gaming				-0.773
				(0.729)
School FE	YES	YES	YES	YES
Personal Controls	YES	YES	YES	YES
Household Controls	YES	YES	YES	YES
Observations	4,088	4,088	4,088	4,088
R-squared	0.334	0.346	0.346	0.360

Notes: The dependent variable is the standard test score for all regressions. The set of personal controls includes student's own 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 and whether he or she lives at school. The set of household controls includes household economic condition, mother's education and father's education. All the standard errors are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 14: Peer Effects on Class Environment: First Year

	Friendly-2013	Learning-2013	Average Index-2013	FPC-2013
Proportion of Migrant Peers	-0.197**	-0.271*	-0.234**	-0.914**
	(0.0886)	(0.137)	(0.106)	(0.412)
Proportion of Left-Behind Peers	-0.392***	-0.743***	-0.568***	-2.194***
	(0.106)	(0.237)	(0.155)	(0.594)
School FE	YES	YES	YES	YES
Personal Controls	YES	YES	YES	YES
Household Controls	YES	YES	YES	YES
Observations	4,005	4,005	4,005	4,005
R-squared	0.048	0.125	0.109	0.106

Notes: The dependent variables are respectively the indicator of whether the classmates are friendly to the student, the indicator of whether the learning environment is good and two combined indexes of the first two indicators. All the regressions in this table are run on the samples from the first year (2013). The set of personal controls includes student's own 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 and whether he or she lives at school. The set of household controls includes household economic condition, mother's education and father's education. All the standard errors are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 15: Peer Effects on Class Environment: Second Year

	Friendly-2014	Learning-2014	Average Index-2014	FPC-2014
Proportion of Migrant Peers	-0.000667	-0.324	-0.162	-0.586
	(0.0436)	(0.205)	(0.113)	(0.421)
Proportion of Left-Behind Peers	-0.429***	-0.509***	-0.469***	-1.881***
	(0.0830)	(0.141)	(0.105)	(0.411)
School FE	YES	YES	YES	YES
Personal Controls	YES	YES	YES	YES
Household Controls	YES	YES	YES	YES
Observations	4,005	4,005	4,005	4,005
R-squared	0.075	0.112	0.114	0.111

Notes: The dependent variables are respectively the indicator of whether the classmates are friendly to the student, the indicator of whether the learning environment is good and two combined indexes of the first two indicators. All the regressions in this table are run on the samples from the second year (2014). The set of personal controls includes student's own 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 and whether he or she lives at school. The set of household controls includes household economic condition, mother's education and father's education. All the standard errors are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 16: Adding Class Environment in the Main Regression: First Year

	(1)	(2)	(3)	(4)
Proportion of Migrant Peers	-0.999**	-0.578*	-0.567*	-0.499*
	(0.383)	(0.296)	(0.296)	(0.297)
Proportion of Left-Behind Peers	-2.157***	-1.104	-1.088	-1.039
	(0.808)	(0.784)	(0.782)	(0.773)
Average of Environment Average Index		1.589***		
		(0.468)		
Average of Environment FPC Index			0.417***	
			(0.120)	
Average Classmates' Relation				1.565***
				(0.575)
Average Learning Environment				0.439
				(0.312)
School FE	YES	YES	YES	YES
Personal Controls	YES	YES	YES	YES
Household Controls	YES	YES	YES	YES
Observations	4,005	4,005	4,005	4,005
R-squared	0.358	0.366	0.366	0.367

Notes: The dependent variable is the standard test score for all regressions. The average classroom environment indicators are calculated by the means of the corresponding variable for all of student *i*'s classmates. All the regressions in this table are run on the samples from the first year (2013). The set of personal controls includes student's own 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 and whether he or she lives at school. The set of household controls includes household economic condition, mother's education and father's education. All the standard errors are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 17: Adding Class Environment in the Main Regression: Second Year

	(1)	(2)	(3)	(4)
Proportion of Migrant Peers	-0.0283	0.263	0.235	0.331
	(0.328)	(0.277)	(0.271)	(0.338)
Proportion of Left-Behind Peers	-1.012***	-0.0779	-0.0537	-0.163
	(0.335)	(0.228)	(0.234)	(0.245)
Average of Environment Average Index		1.911***		
		(0.435)		
Average of Environment FPC Index			0.483***	
			(0.111)	
Average Classmates' Relation				0.599
				(0.554)
Average Learning Environment				1.156***
				(0.343)
School FE	YES	YES	YES	YES
Personal Controls	YES	YES	YES	YES
Household Controls	YES	YES	YES	YES
Observations	4,005	4,005	4,005	4,005
R-squared	0.330	0.362	0.362	0.363

Notes: The dependent variable is the standard test score for all regressions. The average classroom environment indicators are calculated by the means of the corresponding variable for all of student *i*'s classmates. All the regressions in this table are run on the samples from the second year (2014). The set of personal controls includes student's own 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 and whether he or she lives at school. The set of household controls includes household economic condition, mother's education and father's education. All the standard errors are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 18: Long-term Migrant Students' Peer Effect

	(1)	(2)
Proportion of Migrant Peers	-1.058*	0.106
	(0.551)	(0.325)
Proportion of Left-Behind Peers	-1.242	-0.928**
	(0.841)	(0.425)
Proportion of Migrant Peers (more than five years)	0.958	-0.393
	(0.663)	(0.519)
School FE	YES	YES
Personal Controls	YES	YES
Household Controls	YES	YES
Observations	4,072	4,072
R-squared	0.319	0.337

Notes: The dependent variable is the standard test score for all regressions. I add the proportion of migrant students who migrate for more than five years in the regression. The set of personal controls includes student's own 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 and whether he or she lives at school. The set of household controls includes household economic condition, mother's education and father's education. All the standard errors are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 19: Peer Effects Netting Out Average Family Background

	(1)	(2)	(3)	(4)	(5)
Proportion of Migrant Peers	-0.545*	-0.571**	-0.296	-0.351	-0.344
	(0.286)	(0.282)	(0.293)	(0.267)	(0.273)
Proportion of Left-Behind Peers	-1.061**	-0.812*	-0.701**	-0.732**	-0.606*
	(0.432)	(0.447)	(0.321)	(0.336)	(0.354)
Average Socioeconomic Condition of Classmates		0.511*			0.257
		(0.290)			(0.306)
Average Father Education of Classmates			0.142***		0.0763
			(0.0404)		(0.0671)
Average Mother Education of Classmates				0.127***	0.0521
				(0.0325)	(0.0548)
School FE	YES	YES	YES	YES	YES
Year Dummy	YES	YES	YES	YES	YES
Personal Controls	YES	YES	YES	YES	YES
Household Controls	YES	YES	YES	YES	YES
Observations	11,519	11,519	11,519	11,519	11,519
R-squared	0.314	0.319	0.322	0.321	0.324

Notes: The dependent variable is the standard test score for all regressions. The first column is the baseline estimate from the main regression. In columns (2), (3), (4) and (5), I run regressions adding average family background characteristics of the classmates one by one. In column (5), I run regression with the whole set of family background characteristics. The set of personal controls includes student's own 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 and whether he or she lives at school. The set of household controls includes household economic condition, mother's education and father's education. All the standard errors are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 20: Peer Effects Netting Out Average Previous Test Scores: Second Year

	(1)	(2)
Proportion of Migrant Peers	0.294	0.854
	(0.744)	(0.573)
Proportion of Left-Behind Peers	-0.946*	-0.669*
	(0.530)	(0.350)
Average Score of Migrant Peers in 2013		0.156
		(0.101)
Average Score of Left-behind Peers in 2013		0.385*
		(0.228)
School-Grade FE	YES	YES
Personal Controls	YES	YES
Household Controls	YES	YES
Observations	3,654	3,654
R-squared	0.356	0.383

Notes: The dependent variable is the standard test score for all regressions. The set of regressions in this table are run on the sample from the second year. The first column is the baseline estimate when I do not control for previous year's average test scores of migrant peers and left-behind peers. In columns (2), I run regressions adding average test scores of migrant peers and left-behind peers. The set of personal controls includes student's own 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 and whether he or she lives at school. The set of household controls includes household economic condition, mother's education and father's education. All the standard errors are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 21: Robustness: Using School-Level Performance Measurement

	Chinese			Math			English		
	(1) Both Years	(2) First Year	(3) Second Year	(4) Both Years	(5) First Year	(6) Second Year	(7) Both Years	(8) First Year	(9) Second Year
Proportion of Migrant Peers	-5.767**	-12.26**	-2.914	-1.637	-5.352	-1.106	-4.124	-6.577	-4.789
	(2.309)	(4.992)	(2.785)	(4.779)	(5.600)	(5.836)	(2.902)	(4.777)	(3.828)
Proportion of Left-Behind Peers	-11.50**	-24.48**	-8.003***	-16.36***	-33.45***	-12.26**	-16.41***	-29.52***	-13.69***
	(4.442)	(9.550)	(2.991)	(5.459)	(11.67)	(5.834)	(4.746)	(10.17)	(3.829)
School FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year Dummy	YES	NO	NO	YES	NO	NO	YES	NO	NO
Personal Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Household Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	8,144	4,072	4,072	8,144	4,072	4,072	8,144	4,072	4,072
R-squared	0.133	0.145	0.132	0.064	0.072	0.071	0.144	0.158	0.140

Notes: The dependent variablea are the school-level standardized test scores. Three different school-level performance measurements are considered. The first three columns are test scores of Chinese. The next three columns are test scores of Math. The last three columns are test scores of English. For columns (1), (4) and (7), I use data from both years. For columns (2), (5) and (8), I use data from only the first year. For column (3), I use data from only the second year. The set of personal controls includes student's own 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 and whether he or she lives at school. The set of household controls includes household economic condition, mother's education and father's education. All the standard errors are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 22: Robustness: Consider Rural Migrants and Rural Left-Behind

	(1) Both Years	(2) First Year	(3) Second Year
Proportion of Rural Migrant Peers	-0.305	-1.123***	0.379
	(0.375)	(0.374)	(0.517)
Proportion of Rural Left-Behind Peers	-1.226***	-1.757***	-1.084***
	(0.358)	(0.632)	(0.304)
School FE	YES	YES	YES
Year Dummy	YES	YES	YES
Personal Controls	YES	YES	YES
Household Controls	YES	YES	YES
Observations	8,144	4,072	4,072
R-squared	0.336	0.358	0.334

Notes: The dependent variable is the standard test score for all regressions. For column (1), I use data from both years. For column (2), I use data from only the first year. For column (3), I use data from only the second year. The set of personal controls includes student's own 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 and whether he or she lives at school. The set of household controls includes household economic condition, mother's education and father's education. All the standard errors are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 23: Robustness: Left-Behind Children with Both Parents Absent

	(1) Both Years	(2) First Year	(3) Second Year
Proportion of Migrant Peers	-0.212	-0.531**	0.0397
	(0.235)	(0.217)	(0.327)
Proportion of Left-Behind Peers	-1.460***	-2.237***	-1.058***
	(0.447)	(0.631)	(0.373)
School FE	YES	YES	YES
Year Dummy	YES	NO	NO
Personal Controls	YES	YES	YES
Household Controls	YES	YES	YES
Observations	8,144	4,072	4,072
R-squared	0.336	0.359	0.332

Notes: The dependent variable is the standard test score for all regressions. In this table, I alter the definition of left-behind children to be children whose parents are both absent. For column (1), I use data from both years. For column (2), I use data from only the first year. For column (3), I use data from only the second year. The set of personal controls includes student's own 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 and whether he or she lives at school. The set of household controls includes household economic condition, mother's education and father's education. All the standard errors are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 24: Robustness: Only on Ordinary Locals

	(1) Both Years	(2) First Year	(3) Second Year
Proportion of Migrant Peers	-0.586	-1.179	-0.456
	(0.764)	(1.082)	(0.832)
Proportion of Left-Behind Peers	-1.308***	-2.098**	-1.006***
	(0.410)	(1.009)	(0.251)
School FE	YES	YES	YES
Year Dummy	YES	NO	NO
Personal Controls	YES	YES	YES
Household Controls	NO	YES	YES
Observations	4,968	2,484	2,484
R-squared	0.339	0.353	0.346

Notes: The dependent variable is the standard test score for all regressions. In this table, I keep only ordinary local students who are neither migrant nor left-behind students. For column (1), I use data from both years. For column (2), I use data from only the first year. For column (3), I use data from only the second year. The set of personal controls includes student's own age, gender, hukou type, whether he or she is the only child and whether he or she lives at school. The set of household controls includes household economic condition, mother's education and father's education. All the standard errors are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

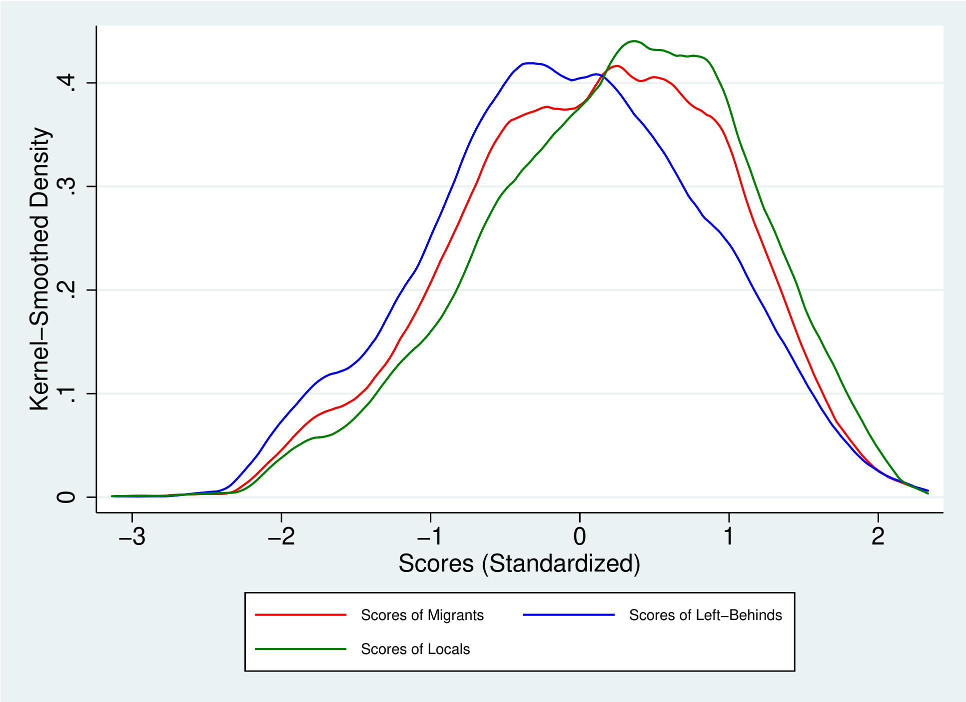


Figure 1: Cognitive Test Score Distributions of Different Types of Students

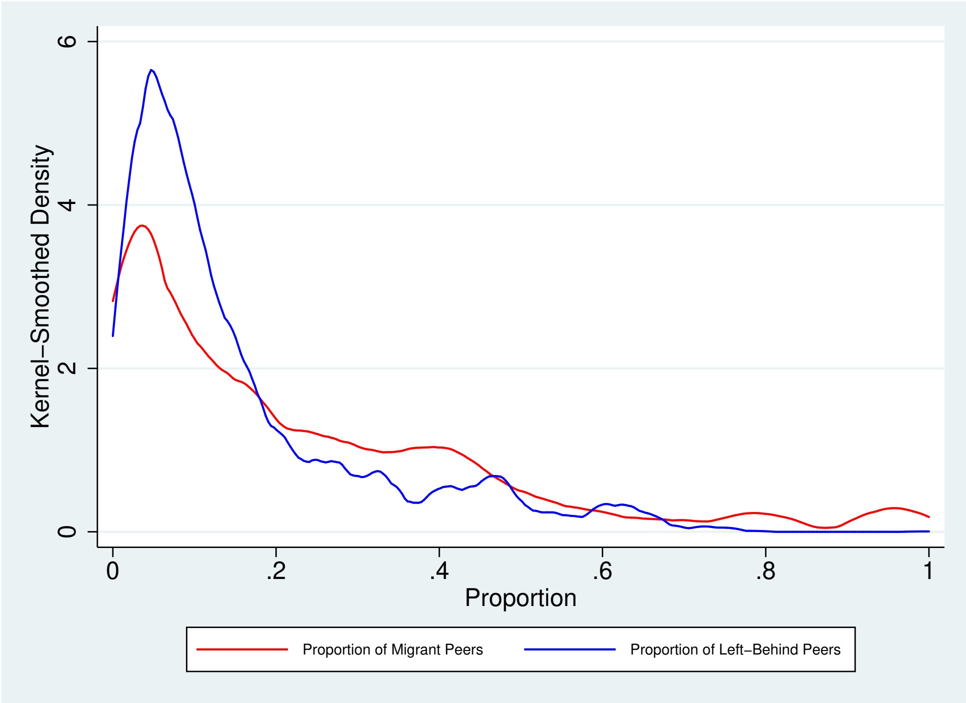


Figure 2: Distributions of Proportions of Migrant/Left-Behind Peers

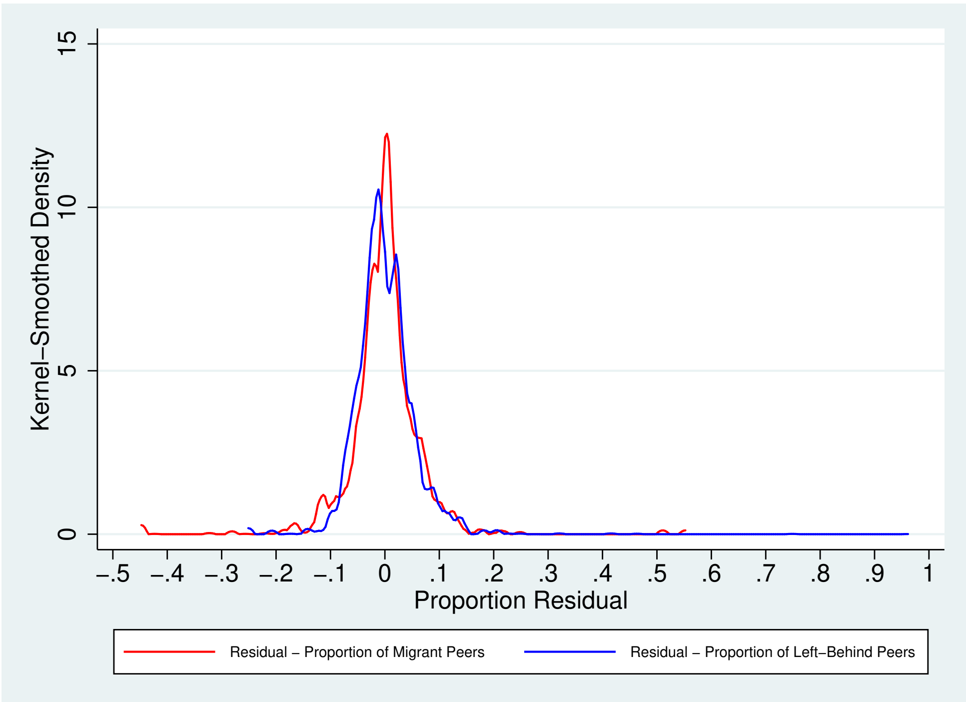


Figure 3: Distributions of Residulized Proportions of Migrant/Left-Behind Peers

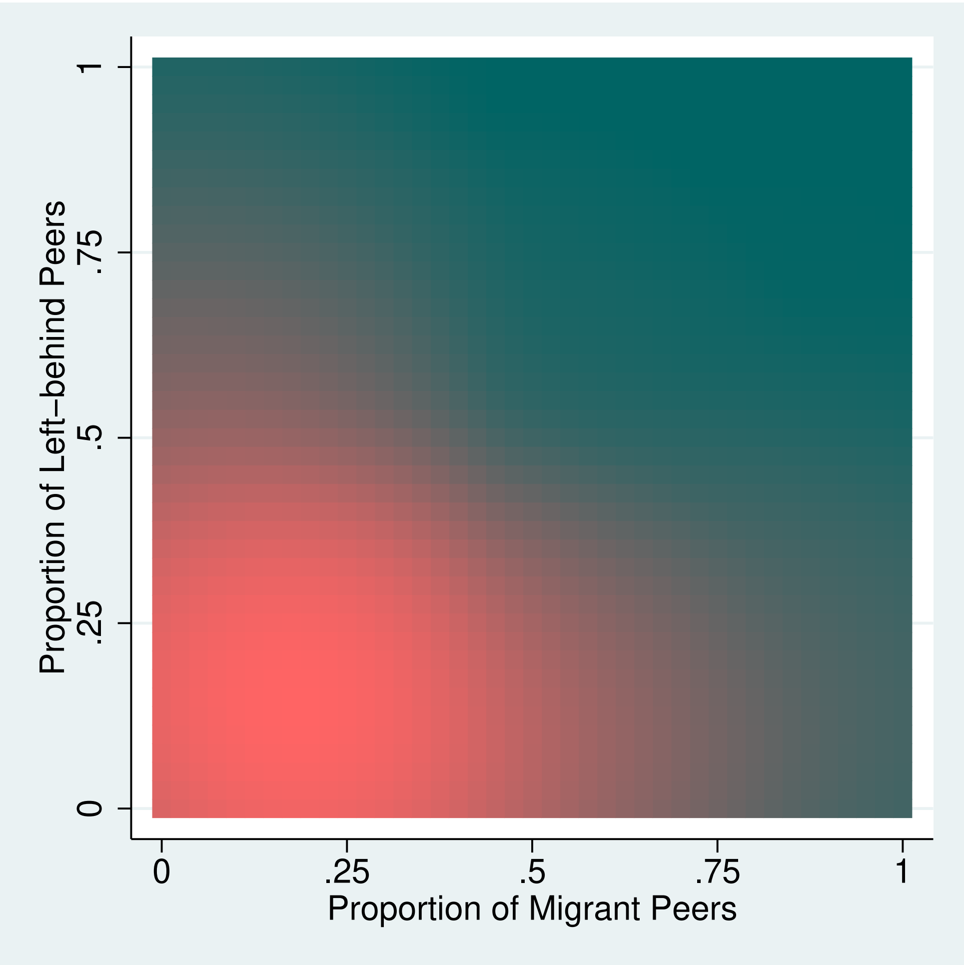


Figure 4: Joint Distribution of Proportions of Migrant/Left-Behind Peers

Appendix

A Baseline OLS Regressions Without School Fixed Effects

Table A1: Peer Effects of Migrant Children and Left-Behind Children Without School Fixed Effects

	(1)	(2)	(3)
Proportion of Migrant Peers	-0.766**	-0.753**	-0.761***
	(0.347)	(0.288)	(0.269)
Proportion of Left-Behind Peers	-1.280***	-0.645***	-0.483**
	(0.290)	(0.215)	(0.200)
School FE	NO	NO	NO
Year Dummy	YES	YES	YES
Personal Controls	NO	YES	YES
Household Controls	NO	NO	YES
Observations	11,519	11,519	11,519
R-squared	0.092	0.161	0.183

Notes: The dependent variable is the standard test score for all regressions. I do not include school fixed effects in any of the regressions in this table. For column (1), I do not control for personal characteristics and household characteristics. For column (2), I do not control for household characteristics. For column (3), I control for all sets of variables. The set of personal controls includes student's own 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 and whether he or she lives at school. The set of household controls includes household economic condition, mother's education and father's education. All the standard errors are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

B Regressions for Classes Without Dropouts

To falsify the alternative story about the reduction of the peer effect in the second wave, I run the regressions in Table 7 on a sample without students who drop out of the school in the second wave. That is, to make sure the results are not driven by the leaving of these dropouts in 2014, I drop all classes with dropouts. Table B1 shows that the changes of the point estimates are small. The estimates of the second wave become more negative, but all the qualitative conclusions persist. The peer effect of migrant classmates is erased and the peer effect of left-behind classmates is reduced in the regression on samples from the second year.

C Peer Effects by Student Ability

One arguable aspect of the peer effect is its heterogeneity on students with different abilities. Who will be affected more, students with high abilities or students with low abilities? To

Table B1: Classes Without Dropouts

	(1) First Year	(2) Second Year	(3) Second Year
Proportion of Migrant Peers	-0.828**	-0.443	-0.0604
	(0.335)	(0.316)	(0.231)
Proportion of Left-Behind Peers	-2.309	-1.545*	-0.967*
	(1.413)	(0.782)	(0.504)
Test Score in 2013			0.432***
			(0.0320)
School-Grade FE	YES	YES	YES
Personal Controls	YES	YES	YES
Household Controls	YES	YES	YES
Observations	3,488	3,488	3,488
R-squared	0.272	0.281	0.438

Notes: The dependent variable is the standard test score for all regressions. In this table, I exclude all classes with students who drop out of school. For column (1), I use data from the first year. For columns (2)—(3), I use the data of the same group of people from the second year. The set of personal controls includes student's own 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 and whether he or she lives at school. The set of household controls includes household economic condition, mother's education and father's education. All the standard errors are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

investigate this question, I first categorize observations into four quartile groups according to their previous period test scores and then run the main regressions with interaction terms of different proportions of peers and quartile group indicators. The baseline group is the fourth quartile group, which is the group of students with highest abilities. In all regressions, I control for the previous period test scores, which leads to a conventional value-added style model. The sample only contains observations from the second year.

The results of the regressions are shown in Table C1. For convenience, I calculate all the marginal effects of proportions of migrant peers and left-behind peers on various quartile groups of students by adding up the corresponding regression coefficients and show them in Table C2. A Wald test is implemented for each of the marginal effects. I find that the proportion of left-behind peers can negatively affect students in each quartile group except for the fourth quartile group but it fades away as the ability of the student becomes higher. For instance, in column (2), an increase of ten percentage points in the proportion of left-behind peers will result in a 0.0883 (0.0390+0.0493) points decrease in the standard test score for students with the lowest previous test scores. The effect shrinks to 0.0597 for students in the second quartile, 0.0592 for students in the third quartile and 0.0202 for students in the fourth quartile. Meanwhile, the

Table C1: Heterogeneous Peer Effects of Migrant Children and Left-behind Children by Ability

	(1)	(2)
Proportion of Migrant Peers	0.245	0.255
	(0.304)	(0.313)
Proportion of Left-Behind Peers	-0.393	-0.390
	(0.324)	(0.323)
Proportion of Migrant Peers # Cognitive Skill Q1	-0.193	-0.208
	(0.236)	(0.242)
Proportion of Left-Behind Peers # Cognitive Skill Q1	-0.506	-0.493
	(0.333)	(0.341)
Proportion of Migrant Peers # Cognitive Skill Q2	0.144	0.136
	(0.257)	(0.260)
Proportion of Left-Behind Peers # Cognitive Skill Q2	-0.244	-0.207
	(0.329)	(0.336)
Proportion of Migrant Peers # Cognitive Skill Q3	0.111	0.102
	(0.186)	(0.180)
Proportion of Left-Behind Peers # Cognitive Skill Q3	-0.243	-0.202
	(0.215)	(0.229)
Test Score in 2013	0.438***	0.432***
	(0.0344)	(0.0342)
School FE	YES	YES
Personal Controls	YES	YES
Household Controls	NO	YES
Observations	4,088	4,088
R-squared	0.486	0.491

Notes: The dependent variable is the standard test score for all regressions. These two regressions use only the sample from the second wave since the previous test scores are available only for the second wave. The set of personal controls includes student's own 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 and whether he or she lives at school. The set of household controls includes household economic condition, mother's education and father's education. All the standard errors are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

proportion of migrant peers only insignificantly affects the scores of students in any quartile and the magnitudes are much smaller. In fact, in the second year, in most of the cases, the proportion of migrant peers can positively affect a student with ability higher than the bottom quartile.

A general conclusion is that in the second year (when the class of 2016 are in grade 8), students in the lowest quartile group of ability are negatively affected the most by the left-behind peers in the class and the effect gets smaller for students with higher abilities. Migrant students will not negatively affect students in any quartile group of ability.

D More Robustness Checks

Table D1 and D2 show the results when I alter sample of the regression. In the survey of CEPS, they use three different sampling frames. In the national core frame, they randomly choose 15 counties from 2,870 counties in the whole country. In the Shanghai frame, they choose 3 out of

Table C2: Marginal Peer Effects of Migrant Children and Left-behind Children by Ability

Marginal Effects	(1)	(2)
Proportion of Migrant Peers on Q1	-0.052	0.047
Proportion of Migrant Peers on Q2	0.389	0.391
Proportion of Migrant Peers on Q3	0.356	0.357
Proportion of Migrant Peers on Q4	0.245	0.255
Proportion of Left-Behind Peers on Q1	-0.899***	-0.883***
Proportion of Left-Behind Peers on Q2	-0.637**	-0.597**
Proportion of Left-Behind Peers on Q3	-0.636**	-0.592**
Proportion of Left-Behind Peers on Q4	-0.393	-0.202

Notes: The marginal effects are calculated in regressions from Table C1. Wald tests are implemented and H_0 is whether the marginal effect is zero. All the standard errors are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

18 counties in Shanghai in addition to the national core sample. In the complementary frame, they choose 10 out of 120 counties with plentiful migrants across the country. In the previous main regressions, I use survey sampling weights to correct the over-sampling. In Table D1, I exclude all samples from the Shanghai frame and the complementary frame, keeping only the national core sample. In Table D2, I drop all samples from Shanghai frame. The results are consistent and robust. In addition, in the main context, I utilize sampling weights when running regressions. Table D3 shows the regression results when I do not use sampling weights. The main conclusions still hold in this setting.

Another concern is that the results in private schools may be very different from the results in public schools and that the negative effects are driven by the students in private migrant schools. To alleviate this problem, I run regressions on the sample of students only in public schools in Table D4, which shows no change in the estimates.

One drawback of the CEPS data set is that it only provides Hukou information at county level and therefore I have to define migrant students as students from another county. Although it is usually very hard to change Hukou registration place, it is still relatively easier to change it across counties in the same city. Actually, I do detect some changes during the two waves (588 out of 11,519 observations). It could be attributed to a real Hukou change or some measurement error. It is possible that the reduction of the peer effects of migrant students in the second year is due to that some migrant students change their Hukou become local in the second wave.

To make sure the patterns of migrant students' spillovers across time are not driven by this, I redefine all students' Hukou registration places as the ones in the first year. That is, even if a student changes his/her Hukou in the second year, I still consider him or her as a migrant student since after all, he or she comes from another place. The results are shown in Table D5. Column two in Table D5 is exactly column one in Table 7 since the migration status are fixed at the value of the first year. In column three I can see that, after redefining, I still detect zero peer effects from migrant students in the second year. In addition to the Hukou status change, left-behind status could also change across time since parents may migrate out or return back home in the second year. Since left-behind status is not a fixed identity as migrant children with a different predetermined hometown, it is more reasonable to make this left-behind status time-variant as in my main context. However, it could be also interesting to see whether the results would change if I keep the identity of both migrant and left-behind students not changed and run the same regressions. The results are shown in Table D6. It shows the same pattern that the negative spillovers are reduced in the second year and the effects from the migrant students decline more. Yet, in this setting, migrant students still have negative peer effect in the second year.

One of the specific concerns in Angrist (2014) is that the regression coefficient may be a result of measurement error on migrant/left-behind status of students rather than the real peer effects. I implement a simulation inspired by Carrell, Hoekstra, and Kuka (2018) and Feld and Zölitz (2017) to further test whether this is the case or not in my setting. The basic idea of the simulation is to add measurement error to the sample and if there is attenuation in the estimation rather than amplification, then I can rule out this concern. The detailed algorithm is as follows: (1) First, randomly select $p\%$ of the sample. (2) Second, in the selected sample, randomly assign 22% of them to be migrant students and 15% of them to be left-behind students (the proportion of migrant and left-behind students in this random assignment are the same to the proportions in the original whole sample). These observations are measured with random error. (3) Third, re-calculate proportions of migrant and left-behind peers in each class using the whole sample. (4) Fourth, run the main regression using the whole sample. I repeat this process for p changing from 0 to 1 where 0 means the baseline estimates without any added measurement error and 1 means the extreme case when all observations are measured with error. Figure 5 shows the results. It is evident that when additional measurement errors are introduced, the estimation of the peer effects are attenuated towards zero. Meanwhile, most of the estimates become statistically not significant.

In the main context, I find that the negative spillovers from migrant students are erased in the second year and claim that it is because they integrate into the classroom better. However, there is another possible reason for the reduction of peer effects in the second year. Parents of the students in classes with many migrant peers may be aware of the negative spillovers after the first year and then devote more money and time on their children to compensate for these spillovers, which leads to the reduction of the coefficient in the second year. To test whether this is true, I take parents' time spend on children and education expenditure of out-of-school courses as the dependent variables and run the regression of them on the proportion of migrant and left-behind peers in their children's class. Table D7 shows that there is no significant changes in parents' investment in their children during the two years. Parents from classes with more migrant students seem to spend less time on their children and more money on their out-of-school courses in the second year. However, nothing is statistically significant from zero.

Table D1: Robustness: Using Only National Core Samples

	(1) Both Years	(2) First Year	(3) Second Year
Proportion of Migrant Peers	-0.391	-1.039**	-0.0282
	(0.285)	(0.403)	(0.346)
Proportion of Left-Behind Peers	-1.349***	-2.228**	-1.061***
	(0.415)	(0.839)	(0.316)
School FE	YES	YES	YES
Year Dummy	YES	NO	NO
Personal Controls	YES	YES	YES
Household Controls	YES	YES	YES
Observations	4,034	2,017	2,017
R-squared	0.336	0.364	0.327

Notes: The dependent variable is the standard test score for all regressions. In this table, I use only national core sample. For column (1), I use data from both years. For column (2), I use data from only the first year. For column (3), I use data from only the second year. The set of personal controls includes student's own 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 and whether he or she lives at school. The set of household controls includes household economic condition, mother's education and father's education. All the standard errors are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table D2: Robustness: Dropping Shanghai Samples

	(1) Both Years	(2) First Year	(3) Second Year
Proportion of Migrant Peers	-0.364	-0.993**	-0.0185
	(0.273)	(0.380)	(0.334)
Proportion of Left-Behind Peers	-1.289***	-2.095**	-1.055***
	(0.403)	(0.806)	(0.311)
School FE	YES	YES	YES
Year Dummy	YES	NO	NO
Personal Controls	YES	YES	YES
Household Controls	NO	YES	YES
Observations	7,282	3,641	3,641
R-squared	0.335	0.357	0.331

Notes: The dependent variable is the standard test score for all regressions. In this table, I drop all observations from Shanghai sample. For column (1), I use data from both years. For column (2), I use data from only the first year. For column (3), I use data from only the second year. The set of personal controls includes student's own 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 and whether he or she lives at school. The set of household controls includes household economic condition, mother's education and father's education. All the standard errors are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table D3: Robustness: No Sampling Weights

	(1) Both Years	(2) First Year	(3) Second Year
Proportion of Migrant Peers	-0.137	-0.544	-0.0652
	(0.229)	(0.335)	(0.216)
Proportion of Left-Behind Peers	-0.867*	-1.158	-0.926**
	(0.467)	(0.839)	(0.427)
School FE	YES	YES	YES
Year Dummy	YES	NO	NO
Personal Controls	YES	YES	YES
Household Controls	NO	YES	YES
Observations	8,144	4,072	4,072
R-squared	0.321	0.318	0.337

Notes: The dependent variable is the standard test score for all regressions. In this table, I run the regressions without utilizing sampling weights. For column (1), I use data from both years. For column (2), I use data from only the first year. For column (3), I use data from only the second year. The set of personal controls includes student's own 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 and whether he or she lives at school. The set of household controls includes household economic condition, mother's education and father's education. All the standard errors are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table D4: Robustness: Samples in Public Schools

	(1) Both Years	(2) First Year	(3) Second Year
Proportion of Migrant Peers	-0.120	-1.209	0.351
	(0.591)	(0.766)	(0.734)
Proportion of Left-Behind Peers	-1.231***	-2.053**	-1.117***
	(0.420)	(0.847)	(0.290)
School FE	YES	YES	YES
Year Dummy	YES	NO	NO
Personal Controls	YES	YES	YES
Household Controls	NO	YES	YES
Observations	7,500	3,750	3,750
R-squared	0.337	0.353	0.340

Notes: The dependent variable is the standard test score for all regressions. In this table, I keep only students in public schools. For column (1), I use data from both years. For column (2), I use data from only the first year. For column (3), I use data from only the second year. The set of personal controls includes student's own 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 and whether he or she lives at school. The set of household controls includes household economic condition, mother's education and father's education. All the standard errors are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table D5: Robustness: Fixing Hukou Status for All Students

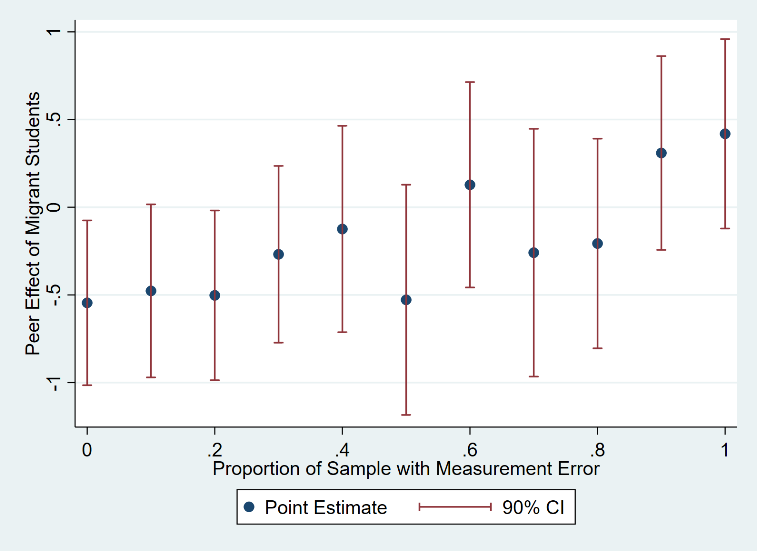
	(1) Both Years	(2) First Year	(3) Second Year
Proportion of Migrant Peers	-0.360*	-0.976**	-0.0579
	(0.209)	(0.371)	(0.193)
Proportion of Left-Behind Peers	-1.243***	-2.062**	-1.050***
	(0.381)	(0.792)	(0.296)
School FE	YES	YES	YES
Year Dummy	YES	NO	NO
Personal Controls	YES	YES	YES
Household Controls	NO	YES	YES
Observations	8,144	4,072	4,072
R-squared	0.338	0.359	0.334

Notes: The dependent variable is the standard test score for all regressions. In this table, I keep only ordinary local students. For column (1), I use data from both years. For column (2), I use data from only the first year. For column (3), I use data from only the second year. The set of personal controls includes student's own age, gender, hukou type, whether he or she is the only child and whether he or she lives at school. The set of household controls includes household economic condition, mother's education and father's education. All the standard errors are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

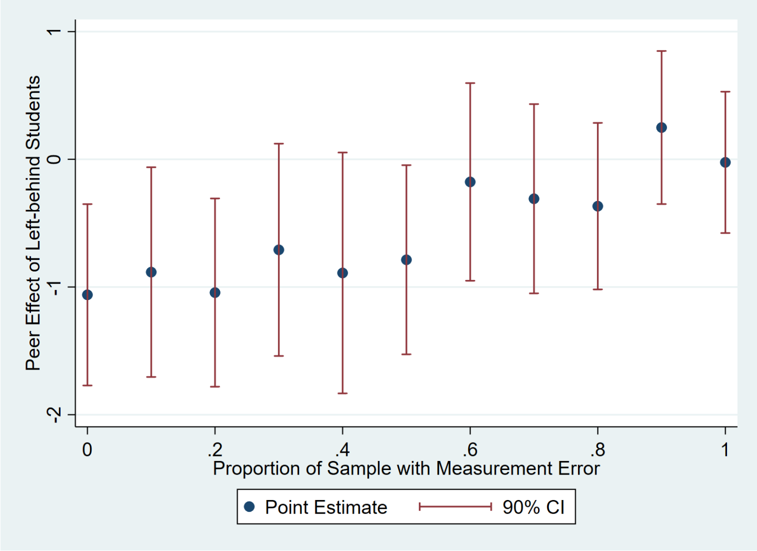
Table D6: Robustness: Fixing Hukou and Left-behind Status for All Students

	(1) Both Years	(2) First Year	(3) Second Year
Proportion of Migrant Peers	-0.702***	-0.976**	-0.519**
	(0.253)	(0.371)	(0.201)
Proportion of Left-Behind Peers	-1.947***	-2.062**	-1.895***
	(0.649)	(0.792)	(0.688)
School FE	YES	YES	YES
Year Dummy	YES	NO	NO
Personal Controls	YES	YES	YES
Household Controls	NO	YES	YES
Observations	8,144	4,072	4,072
R-squared	0.346	0.359	0.348

Notes: The dependent variable is the standard test score for all regressions. In this table, I keep only ordinary local students. For column (1), I use data from both years. For column (2), I use data from only the first year. For column (3), I use data from only the second year. The set of personal controls includes student's own age, gender, hukou type, whether he or she is the only child and whether he or she lives at school. The set of household controls includes household economic condition, mother's education and father's education. All the standard errors are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.



(a) Peer Effects of Migrant Students



(b) Peer Effects of Left-behind Students

Figure 5: Main Regression Coefficients with Simulated Samples

Table D7: Robustness: Parents' Investment

Dependent Variable	Time Spend on Children		Education Expenditure	
	(1) First Years	(2) Second Year	(3) First Year	(4) Second Year
Proportion of Migrant Peers	-1.060	-3.720	-670.7	212.6
	(0.911)	(3.463)	(489.4)	(442.3)
Proportion of Left-Behind Peers	0.802	4.712***	-520.1	-247.9
	(1.895)	(0.705)	(991.9)	(314.4)
School FE	YES	YES	YES	YES
Personal Controls	YES	YES	YES	YES
Household Controls	YES	YES	YES	YES
Observations	3,358	3,358	3,358	3,358
R-squared	0.073	0.067	0.198	0.254

Notes: The dependent variable is the standard test score for all regressions. In this table, I keep only ordinary local students. For column (1), I use data from both years. For column (2), I use data from only the first year. For column (3), I use data from only the second year. The set of personal controls includes student's own age, gender, hukou type, whether he or she is the only child and whether he or she lives at school. The set of household controls includes household economic condition, mother's education and father's education. All the standard errors are clustered at the school level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.