Left-Behind Children's Educational Performance Drops Slightly After Parents Migrated

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Abstract

Millions of children worldwide are "left behind" when their parents migrate away for work. Parents' labor migration increases household income but decreases parental care, thereby exerting mixed influences on child development, including educational performance. To what extent do different arrangements of parental migration affect children's schooling performance in the short term? Studying the case of China, I obtained a sample of four thousand junior high school students from a nationally representative two-wave panel survey. I differentiated household migration arrangements of any one parent, of mother only, of father only, and of both parents. I measured children's educational performance by standardized cognitive test score and academic exam grades. For causal inference, I built difference-in-differences models with propensity score matching. Results show that the new left-behind children's performance at school dropped slightly compared to that of non-left-behind peers. Father-only migration is negatively associated with children's cognitive abilities, while mother-only migration is negatively associated with children's academic grades.

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Introduction

Worldwide, millions of children are resided in their home communities but separated from their parents as either one or both parents have migrated for work. These are the so-called "left-behind children" or "stay-behind children." They are common in migrant-sending regions, such as Latin America, Sub-Sahara Africa, East Europe, and large parts of Asia. Researchers estimated that one-sixth of Mexican children (DeWaard et al., 2018), one-fifth of Bulgarian children (Popova, 2018), and one-fourth of Chinese children were living apart from their migrating parents (NBS et al., 2017). In a 2021 resolution, the Council of Europe's Parliamentary Assembly (2021) expressed concern about "the scale of this phenomenon and the long-term damage it creates" (p. 2) and declared that leaving "millions of labour migrants' children without parental care is a mass violation of human rights" (p. 1).

How are stay-behind children faring when parents have migrated? Research results are mixed due to the differential effects of parental migration. Consider children's education. According to the review articles by Brauw (2019) and Van Hook and Glick (2020), labor migrants send remittances back, which can fund children's schooling as well as improve their nutritional and living conditions. The inflow of remittances, however, cannot substitute for the loss of parental care. Parental migration decreases the amount and quality of parental guidance, protection, and support. It is uncertain how these two opposing effects together shape children's educational performance, which merits empirical investigation.

A challenge arises in assessing the causality between parent's migration and children's educational achievement. Experiments can unveil causal relations, but it is unfeasible and unethical to design an experiment that randomly assigns parents to migrate without their children. Alternatively, a quasi-experimental design can help with causal inference. The cause should be on par with random assignment to participants in the analysis, conditional on identification assumptions (Cunningham, 2021).

In this thesis, my research question is: To what extent do different arrangements of parental migration affect the educational performance of left-behind children in the short term? I choose China as the case and analyzed data from a two-wave panel survey. The nationally representative sample includes children in both urban and rural areas. I develop a difference-in-differences model for causal inference and applied propensity score matching for robustness check. The outcome was measured with children's cognitive test score and academic exam scores. I demonstrate that parental migration reduces the educational performance of children staying behind, but only to a small extent.

Literature Review

Theoretical Framework

Between parental migration and children's education, the mechanisms trace to two theoretical frameworks. One is the resource generation model. It holds that parental migration brings forth greater resources in the form of economic capital. Economic capital is, in Bourdieu's words, "immediately and directly convertible into money and may be institutionalized in the form of property rights" (2002, p. 16). Economic capital is transferable to human capital, which is the stock of "skills, talents, health, and expertise" in people that enhance their productivity (Botev et al., 2019; Goldin, 2016). D. Yang (2008) noted that in the Philippines, a sharp depreciation of peso increased the amount of remittances from migrants working abroad. This subsequently boosted children's school enrollment and educational expenditure. In China, Chang et al. (2019) interviewed migrant workers and their family members. Oftentimes, they found that labor migration presented the only way to sustain their children's education and livelihood.

The other theoretical model is the family disruption model. Children flourish under parental nurturing care. This term refers to the "stable environments that promote health and adequate nutrition, protect from threats, and provide opportunities for learning and responsive, emotionally supportive and developmentally enriching relationships" (Black et al., 2021, p. 1). Parental migration decreases nurturing care, as characterized by less homework supervision and emotional support by parents (Wen & Xie, 2019). Hong talked to a group of left-behind children at a rural school (Hong & Fuller, 2019). These students expressed the utter sense of loneliness "with no advocate, no support and with no one looking out for them" (p. 13). Many of them felt indifferent to grades and disengaged with school. Some even longed to quit school to pursue a free, independent life (p. 14).

Given the two opposing effects, researchers have obtained mixed results regarding how parental migration impacts children's education. Botezat and Pfeiffer (2020) studied the case of Romania and found a positive effect of parents' migration on academic grades of adolescents aged eleven to fifteen. L. Wang et al. (2019) collected data from junior high school students in central China and found no effect of parental on left-behind children's achievement in mathematical test. Studying four Chinese provinces, Brauw and Giles (2017) showed that as ample migration opportunities appeared in villages, enrollment to senior high school decreased. Nguyen (2016) demonstrated that parental migration was associated with lower cognitive capabilities among Indian and Vietnamese children aged five to eight. The inconsistency can be complicated by factors such as the left-behind children's age and gender, the migrant parent's original domicile and eventual destination, and the arrangement of which parent migrate for how long.

Parental migration immediately disrupts family structure, which in turn lowers academic performance of children. It takes longer time for parental migration to generate resources that improve children's educational attainment. I propose the first hypothesis:

H_1 In the short term, parental migration negatively affect the cognitive development and academic performance of children left-behind.

Researchers have studied whether the impact differ between mother absence and father absence induced by labor migration. Y. Xu et al. (2019) adopted a fixed-effects propensity score weighting model on cross-sectional data collected from seventh and ninth graders in rural areas across China. They found that the absence of father only or both parents had "little or no association with negative outcomes" on children's academic and cognitive performances. Only-mother absence, however, showed a "strong association with negative outcomes" (p. 1646). Chen et al. (2019) conducted structural equation modeling on the cross-sectional data collected from fourth to seventh graders in the countryside of one province. They found that mother migration was "negatively associated with children's social competence and academic performance," while father migration had no direct effects on the two outcomes (pp. 860-861).

Studies noted that in some Asian and Latin American societies, the social norms designate men as breadwinners and women as caregivers. Under such norms, children are more likely to accept fathers' migration than mothers' (Murphy, 2022). Left-behind children may even resent their migrant mothers for transgressing on the expected care-giving roles. I propose the second hypothesis:

H_2 In the short term, mother's migration negatively affect the cognitive development and academic performance of children left-behind, while father's migration does not show a effect.

China's Context

Three features make China a suitable case for studying left-behind children. The first feature is the huge scale of internal labor migration. According to the National Bureau of Statistics, the year 2021 recorded 292.5 million in-country migrant workers (NBS, 2022). They form the backbone of essential industries, such as retail, delivery, transportation, and manufacturing. The 2015 one-percent National Population Sample Survey estimated that 68.7 million Chinese children were left behind (NBS et al., 2017). The internal migration stemmed from the neoliberal economic regime.

The neoliberal economic regime sounds at odds with China, a so-called socialist country. Actually, in the 1980s, the ruling communist party ditched the planned economy, initiated market reforms, and opened up the country. Since then, China has integrated in the global economy and contributed substantial growth to it. The economic reform and globalization have enriched the coastal cities like Shanghai and Shenzhen. The rural hinterlands, however, have lagged behind. The regional inequality needs social policy to amend, but China's welfare program is discriminatory – it segregates the population. Those who reap the greatest benefits are public servants, urban dwellers, and formally employed people. As rural people migrate to the city, they find themselves with limited access to social welfare in the destination. The municipal governments only provide welfare to local residents and expect non-local residents access public services elsewhere (Duckett, 2020; Zhang, 2018).

The institutionalized discrimination against migrant laborers find its roots in China's "multilevel citizenship" system. As Vortherms (2021) demonstrated, the constituents of citizenship – "membership rules and rights entitlements" – operate below the national level in China. The local state confers most of the rights and defines who is eligible to these rights through the *hukou*, or household registration system:

> A political institution rooted in centuries of Chinese bureaucracy, the modern hukou is the primary identity document defining membership and entitlements for local citizenship. Accessing fundamental citizenship rights depends on your registration status … Registration includes basic identifying information, a specific address of registration, and a type: urban, rural, or resident. (Vortherms, 2021)

In other words, the hukou system binds one's citizenship rights with one's place of registry. In theory, anyone can move out of town freely. In practice, they cannot change hukou freely. When rural residents move to the city, it takes months – if not years – to apply for a new hukou. Before receiving urban hukou, they can hardly send their children into public schools in the host city (Gu, 2022). Migrant workers have organized petitions, strikes, and protests. These actions often fell on deaf ears and sometimes even ended with police crackdown (Chan, 2019). Facing financial and policy constraints, many migrant laborers have to leave children in their hometowns.

The existing research about China's left-behind children has three major shortcomings. The first is that most literature focuses on children left behind in rural areas while neglecting the urban counterparts. The National Bureau of Statistics stated that the number of urban left-behind children had been growing and expected that the trend would continue (NBS et al., 2017). My sample includes urban left-behind children as well. The second shortcoming lies in sampling and research design. Some studies suffer from a limited sample size of less than one thousand participants or a limited geographic coverage of one to a few towns (Y. Liu et al., 2021; Shu, 2021; F. Yang et al., 2022). Others only estimated correlation using cross-sectional data (Akezhuoli et al., 2022; Jin et al., 2020). These studies could have employed causal inference techniques like fixed effect, matching, or inverse probability of treatment weighting. The third shortcoming lies in the measurement of outcome. Chang et al. (2019) and L. Wang et al. (2019) measured students' educational performance with the test score of only one academic subject, namely mathematics. To tackle these limitations, I adopted a nationally representative two-wave panel dataset. I included the test results of multiple subjects to measure comprehensive academic achievement.

Methods

Sampling

I obtained the data from the China Education Panel Survey (CEPS) (NSRC, n.d.). It is a nationally representative, school-based survey featuring junior high school students. The survey administrator is the National Survey Research Center at Renmin University of China. The survey team adopted multi-stage stratified probability proportional to size sampling and administered a paper-and-pencil questionnaire to each participant. The baseline survey took place in the 2013-2014 academic year with a sample size of about twenty thousand students in the seventh and ninth grades. These students were nested in 438 classrooms of 112 schools in 28 urban districts or rural counties. The follow-up survey in the 2014-2015 academic year lost track of the ninth grade cohort and only surveyed 9449 of the seventh grade cohort. I further restricted the sample to students staying with both parents at the original domicile at the baseline survey. To deal with missing values, I adopted list-wise deletion for dependent, independent, and control variables. The final sample size amounted to 4088 .

Measurement

I explored two categories of educational performance: cognitive and academic abilities. One key dependent variable, the student's cognitive skill, was measured by a fifteen-minute standardized test. The test covered three types of reasoning: verbal, visuospatial, and numerical. The CEPS research team calculated the raw score based on the Item Response Theory and then standardized the score across the whole national sample with a mean of zero and standard deviation of one (W. Wang & Li, 2015).

Another dependent variable concerned students' academic performance. This was measured by the total scores of mid-term exams in Chinese, mathematics, and English as provided by each school. Exam scores are reliable indicators of learning performance, and are comparable across schools for the same cohort of students. This is related to how junior high schools operate as part of the compulsory education system in China. According to OECD (2016), China's junior secondary education is a unified system that does not distinguish between academic and vocational tracks. At school, Chinese, mathematics, and English are core subjects and others as supplementary subjects. Throughout junior high school, students study the core subjects in preparation for the senior high school entrance exam. Within each cohort in one particular school, teachers use the same syllabus and administer the same exams during a given assessment period. Across cities and regions, junior high schools adopt the educational content and assessment set by the Ministry of Education (OECD, 2016).

I transformed the exam grades through the following steps. I first aligned different grading scales (full mark of 100, 120, and 150 for one subject) to the hundred-point scale. After the conversion, I checked for abnormal values outside the 0-100 range. 31 observations were outliers, accounting for less than one percent of the sample. I trimmed the values of subject exam score with minimum of zero and maximum of one hundred. In this way, I can limit the impact of outliers while retaining these observations in the sample. After trimming, I aggregated the subject exam scores to obtain a total score of a 300-point scale.

The key independent variable, the parental migration status, was identified by two items in the parent survey. In both the baseline and the follow-up surveys, parents specified the family members living in the same household at the time. I constructed four treatment dummy variables measuring migration arrangements: any parents absent, only father absent, only mother absent, and both parents absent. These arrangements are mutually exclusive. The control group consisted of parents staying with their children throughout at both the baseline and the follow-up surveys. I then removed the observations that reported parental divorce or death. These type of parental absence are irrelevant to migration.

The control variables on children include their age, gender, ethnicity, self-rated health, hukou type, number of siblings, whether the child had skipped grade or repeated grade, and the level of education that the child aspires to achieve. At the household level, I controlled the level of education of the best-educated parent, the parental expectation on the child's level of education, the perceived household financial conditions, the number of extracurricular books at home, and the internet access at home.

Data analysis

I adopted `R` for all the analyses, the `fixest` package for econometric modeling (Berge et al., 2022), and the `modelsummary` package for presenting the results (Arel-Bundock, 2022). I built a two-way fixed effect model in a difference-in-differences (DID) design, following Bai and colleagues' (2018; 2020) approach. The model served to analyze the educational outcome of children newly left behind by parents vis-a-vis that of children staying together with parents. I first specified an unrestricted and unadjusted model:

$$\Delta score_{i,j,k} = \alpha + \beta \cdot migr_i + \gamma \cdot score_{i,j;1} + \lambda \cdot C_j + \theta \cdot C_k + \varepsilon_{i,j,k}$$

For student i in class j in baseline and class k in endline, $\Delta score_{i,j}$ is the change in test score between baseline and follow-up surveys, $migr_i$ is the treatment dummy variable, $score_{i,j,k;1}$ is the test score at baseline, and C_j and C_k are the classroom fixed-effects at baseline and follow-up, respectively. Classroom fixed-effect can account for differences due to time-invariant factors at the classroom level and above, as students nested in the same class are also in the same school and county. About one-sixth of the students were reassigned into new classroom at the end of baseline academic year. This necessitates adding the wave-two classroom fixed-effect.

The model is unrestricted because it does not restrict on the coefficient associated with the baseline scores. The model is unadjusted as it does not adjust for additional covariates. Theoretically, it is unnecessary to include covariates that vary over group but remain constant over time; They would cancel out in the two-way fixed effect model (Huntington-Klein, 2022). The standard errors were clustered at the classroom level.

In addition, I present an unrestricted and adjusted DID model:

$$\Delta score_{i,j,k} = \alpha + \beta \cdot migr_i + \gamma \cdot score_{i,j,k;1} + \lambda \cdot C_j + \theta \cdot C_k + \zeta \cdot X_i + \varepsilon_{i,j,k}$$

where X_i is the vector of covariates capturing the characteristics of children, their parents, and their households. The control variables were measured in the baseline survey. This version of model lifts the restriction that covariates from the baseline survey would be associated with a coefficient that equals one.

Results

Descriptive Statistics

Table 1 below summarizes the changes in migration status in the sample. All 4088 children were living together with parents in one household in baseline, but about fifteen percent saw at least one parent migrated during the two waves of survey. In these new migrant households, only-mother migration and only-father migration each accounted for two out of five cases. The remaining one-fifth was both-parents migration.

		N	%
Parental Migration	No	3452	84.4
	Yes	636	15.6
Parental Migration Type	Both Parents At Home	3452	84.4
	Both Parents Migrated	131	3.2
	Only Father Migrated	251	6.1
	Only Mother Migrated	254	6.2

Tables 2 below summarizes the dependent variables by the control group and the treatment group. In addition, the violin plots in the appendix visualize the distribution of outcome variables.

	Parental Migration				
	No = 3452		Yes = 636		
Variable	Mean	Sd	Mean	Sd	Test
Cognitive test score difference	0.28	0.8	0.19	0.8	p=0.006**
Wave 1 score	0.15	0.86	0.13	0.84	p=0.471
Wave 2 score	0.43	0.78	0.31	0.8	p<0.001***
Academic exam score difference	-8.2	32.75	-12.15	35.43	p=0.006**
Wave 1 score	213.39	49.31	211.58	50.3	p=0.395
Wave 2 score	205.19	54.83	199.42	58.23	p=0.016*

Note:
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	Parental Migration				
	No = 3452		Yes = 636		
Variable	N	Percent	N	Percent	Test
child.is.girl					X2=11.942***
... 0	1650	48%	352	55%	
... 1	1802	52%	284	45%	
child.has.rural.hukou					X2=0.485
... 0	1884	55%	337	53%	
... 1	1568	45%	299	47%	
child.in.boarding.school					X2=4.63*
... 0	2477	72%	429	67%	
... 1	975	28%	207	33%	
child.is.ethnic.minority					X2=0.388
... 0	3213	93%	587	92%	
... 1	239	7%	49	8%	
child.had.skipped.grade					X2=0.02
... 0	3414	99%	628	99%	
... 1	38	1%	8	1%	
child.had.repeated.grade					X2=10.621**
... 0	3147	91%	553	87%	
... 1	305	9%	83	13%	
child.went.to.preschool					X2=0.923
... 0	531	15%	108	17%	
... 1	2921	85%	528	83%	
parent.has.white.collar.job					X2=0.001
... 0	2735	79%	503	79%	
... 1	717	21%	133	21%	
home.has.internet					X2=12.815***
... 0	1072	31%	244	38%	
... 1	2380	69%	392	62%	

Note:

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	Parental Migration				
	No = 3452		Yes = 636		
Variable	Mean	Sd	Mean	Sd	Test
child.age	12.45	0.63	12.5	0.72	F=3.616
child.health.self.rated	4.17	0.87	4.14	0.9	F=0.622
child.educational.aspiration	3.97	1.12	3.93	1.19	F=0.617
parent.educational.level	2.9	1.19	2.94	1.21	F=0.367
parent.expectation.on.child	4.19	0.91	4.15	0.94	F=1.093
home.extracurricular.book	3.41	1.18	3.32	1.28	F=3.09
home.economic.resource	2.87	0.55	2.84	0.58	F=1.37

Note:
* p < 0.05, ** p < 0.01, *** p < 0.001

Regression Analysis

The unrestricted DID models support my hypothesis one – newly left-behind adolescents are more likely to perform worse in cognitive and academic abilities than their non left-behind counterparts. If a household sees any parent migrated, the child's cognitive test score and total exam grade would decrease relative to that of children whose parents stay with them, holding everything else constant. Parental migration is linked to -0.09 SD in cognitive test score and -0.09 points in academic exam grades. Both relationships are slight in strength.

The results only partially support the hypothesis two – mother migration has a more negative effect than father migration. This holds true for academic abilities. Children from only mother migrate households are associated with -0.04 points relative to that of children whose parents stay along. The performances of children with both parents migrated or only father migrated do not show statistically significant difference from the non left-behind children. Regarding cognitive abilities, the reverse is true. Children with only mother migrated do not show statistically significant difference from the non left-behind children. Children with only father absent are associated with (-0.14 SD), and both parents absent (-0.10 SD) compared to the non left-behind children.

Table 2

Parental migration's effect on children's cognitive test score

	Any Parent Migrated	Only Mother Migrated	Only Father Migrated	Both Parents Migrated
Migration	-0.09**	-0.04	-0.14**	-0.10
	(0.03)	(0.05)	(0.04)	(0.06)
W1 score	-0.62***	-0.63***	-0.62***	-0.62***
	(0.02)	(0.02)	(0.02)	(0.02)
Num.Obs.	4088	3706	3703	3583
R2	0.494	0.502	0.505	0.499
R2 Adj.	0.424	0.426	0.430	0.419
R2 Within	0.370	0.378	0.378	0.374
FE: clsids	X	X	X	X
FE: w2clsids	X	X	X	X

Note: ^^ † $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: ^^ Control variables not included

Table 3

Parental migration's effect on children's academic exam score

	Any Parent Migrated	Only Mother Migrated	Only Father Migrated	Both Parents Migrated
Migration	-2.67*	-5.85*	-0.25	-1.13
	(1.26)	(2.36)	(1.66)	(2.28)
W1 score	0.04	0.04†	0.04†	0.04
	(0.02)	(0.02)	(0.02)	(0.02)
Num.Obs.	4088	3706	3703	3583
R2	0.562	0.577	0.566	0.577
R2 Adj.	0.501	0.513	0.500	0.510
R2 Within	0.005	0.009	0.004	0.004
FE: clsids	X	X	X	X
FE: w2clsids	X	X	X	X

Note: ^^ † $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: ^^ Control variables not included

The adjusted DID models produce similar results compared to the unadjusted models, with only one exception. That is, for the cognitive skills, the both-parent-absent coefficient saw a change of statistical significance level from five percent level to ten percent level.

Some predictors are strong in both models of cognitive and academic abilities. These are children's age and educational aspiration as well as parents' expectation on children. In terms of age, the older students' scores drop relatively more than younger students'. One year older in age is associated with -0.07 SD for standardized cognitive test and -1.23 points for academic exams. Parent's expectation for children completing university and children's own aspiration for finishing university are associated with higher scores. The effect sizes are 0.01 SD and 0.07 SD for standardized cognitive test, respectively; and 0.29 points and 1.82 points for academic exams, respectively.

Several predictors are strong in the model of academic grades but not in that of cognitive scores. These are children's gender and self-reported health, and the years of parental education. Girls outperform boys by 4.49 points in academic exams, but do not show advantage in cognitive test. Students who consider themselves healthier are associated with higher scores in academic exams. Parents with more education are associated with their children's higher scores in academic exams. If the years of parental education of the best-educated among the two increase by one, it would be linked to a 0.88 points increase in the child's academic exam grade. These three predictors are not significant for cognitive outcomes.

Preschool attendance is associated with higher cognitive outcomes 0.07 SD, but its effect for academic outcomes is not significant.

Table 4

Parental migration's effect on children's cognitive test score

	Any Parent Absent	Only Mother Absent	Only Father Absent	Both Parents Absent
Migration	-0.09**	-0.04	-0.14***	-0.08
	(0.03)	(0.05)	(0.04)	(0.06)
W1 score	-0.67***	-0.67***	-0.67***	-0.67***
	(0.02)	(0.02)	(0.02)	(0.02)
child.age	-0.07***	-0.06**	-0.07***	-0.08***
	(0.02)	(0.02)	(0.02)	(0.02)
child.is.girl	-0.01	0.00	0.00	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)
child.health.self.rated	-0.02	-0.02	-0.02	-0.02
	(0.01)	(0.01)	(0.01)	(0.01)
child.has.rural.hukou	-0.01	0.00	-0.01	0.00
	(0.02)	(0.03)	(0.03)	(0.03)
child.number.of.sibling	-0.03	-0.02	-0.02	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)

	Any Parent Absent	Only Mother Absent	Only Father Absent	Both Parents Absent
child.went.to.preschool	0.07*	0.06†	0.05†	0.07*
	(0.03)	(0.03)	(0.03)	(0.03)
child.had.skipped.grade	-0.17	-0.11	-0.20	-0.10
	(0.12)	(0.12)	(0.12)	(0.12)
child.had.repeated.grade	-0.08*	-0.11**	-0.07†	-0.06
	(0.04)	(0.04)	(0.04)	(0.04)
child.in.boarding.school	0.04	0.02	0.02	0.01
	(0.04)	(0.04)	(0.04)	(0.04)
child.educational.aspiration	0.07***	0.07***	0.07***	0.08***
	(0.01)	(0.01)	(0.01)	(0.01)
child.is.ethnic.minority	0.04	0.04	0.02	0.02
	(0.06)	(0.06)	(0.06)	(0.06)
parent.expectation.on.child	0.08***	0.09***	0.09***	0.09***
	(0.02)	(0.02)	(0.02)	(0.02)
parent.has.white.collar.job	0.01	-0.01	0.01	0.00
	(0.03)	(0.03)	(0.03)	(0.03)
parent.educational.level	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
home.economic.resource	-0.02	-0.01	0.00	0.00
	(0.02)	(0.02)	(0.02)	(0.02)
home.extracurricular.book	0.01	0.00	0.01	0.00
	(0.01)	(0.01)	(0.01)	(0.01)
home.has.internet	-0.01	-0.01	-0.02	-0.02
	(0.03)	(0.03)	(0.03)	(0.03)
Num.Obs.	4088	3706	3703	3583
R2	0.525	0.533	0.537	0.530
R2 Adj.	0.458	0.459	0.464	0.452
R2 Within	0.409	0.416	0.418	0.413
FE: clsids	X	X	X	X
FE: w2clsids	X	X	X	X

Note: ^^ † $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5

Parental migration's effect on children's academic exam score

	Any Parent Migrated	Only Mother Migrated	Only Father Migrated	Both Parents Migrated
Migration	-2.65*	-5.87**	-0.20	-0.92
	(1.25)	(2.24)	(1.68)	(2.35)
W1 score	-0.01	-0.01	0.00	-0.01
	(0.02)	(0.03)	(0.02)	(0.02)
child.age	-1.23†	-1.04	-1.21†	-0.96
	(0.65)	(0.68)	(0.70)	(0.70)
child.is.girl	4.49***	4.78***	4.54***	4.43***
	(0.92)	(0.95)	(0.92)	(0.97)
child.health.self.rated	1.05*	1.12*	0.92*	0.85†
	(0.43)	(0.45)	(0.47)	(0.47)
child.has.rural.hukou	1.08	1.50	0.80	0.98
	(1.02)	(1.06)	(1.05)	(1.07)
child.number.of.sibling	1.03†	0.87	1.21*	0.66
	(0.58)	(0.59)	(0.60)	(0.62)
child.went.to.preschool	1.65	2.22†	0.85	1.97
	(1.20)	(1.24)	(1.28)	(1.27)
child.had.skipped.grade	-0.73	0.23	-0.98	1.01
	(4.82)	(4.82)	(5.41)	(5.07)
child.had.repeated.grade	-1.81	-1.22	-1.55	-0.20
	(1.85)	(1.98)	(1.89)	(1.81)
child.in.boarding.school	-1.14	-0.19	-0.72	-1.19
	(1.65)	(1.65)	(1.66)	(1.81)
child.educational.aspiration	1.82***	2.08***	1.90***	1.91***
	(0.52)	(0.55)	(0.51)	(0.53)
child.is.ethnic.minority	0.48	-0.24	-0.33	-1.14
	(2.15)	(2.29)	(2.38)	(2.56)
parent.expectation.on.child	0.88†	0.85	0.86	0.96†
	(0.53)	(0.55)	(0.54)	(0.55)
parent.has.white.collar.job	0.29	0.03	0.59	0.42
	(1.19)	(1.23)	(1.21)	(1.25)
parent.educational.level	1.02†	1.14*	1.14*	1.15*

	Any Parent Migrated	Only Mother Migrated	Only Father Migrated	Both Parents Migrated
	(0.53)	(0.53)	(0.54)	(0.56)
home.economic.resource	-0.74	-0.18	-0.66	-0.24
	(0.81)	(0.88)	(0.87)	(0.87)
home.extracurricular.book	-0.78†	-1.18*	-0.86†	-0.85†
	(0.45)	(0.46)	(0.45)	(0.46)
home.has.internet	-1.41	-1.65	-1.33	-1.37
	(1.13)	(1.14)	(1.18)	(1.17)
Num.Obs.	4088	3706	3703	3583
R2	0.573	0.590	0.578	0.588
R2 Adj.	0.512	0.525	0.512	0.520
R2 Within	0.032	0.039	0.032	0.030
FE: clsids	X	X	X	X
FE: w2clsids	X	X	X	X

Note: ^^ † $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Matching

Parental migration is not a randomly assigned treatment. A possible circumstance is that smart and ambitious students perform better at school; their high performance and ambition prompt parents to migrate to support children's schooling. Another scenario is that poverty may hamper children's educational achievement while driving parents to migrate. To tackle the selection bias herein, an applicable technique is matching. This method makes two groups comparable by pairing a unit in the treatment group with one or several units in the control group based on observable covariates.

Popular choices for matching include coarsened exact matching (CEM) (Waldman, 2022) and nearest-neighbor propensity score matching (PSM) (H. Xu & Xie, 2015). As Greifer (2022) introduced, CEM is superior in achieving balance as it optimizes the entire joint distribution of covariates. The downside is that it leaves many units without an exact match and discards these unmatched units. The nearest-neighbor matching examines all the treated units and selects the closest control unit to be paired. The eligibility as the "closest" can be determined with the differences in propensity score. Propensity score denotes the probability of receiving treatment based on the specified covariates. Nearest-neighbor PSM does not try to optimize any condition; each pairing ignores how other pairing will occur or have occurred (Greifer, 2022). King and Nielsen (2019) argued against this matching method as it risks more "imbalance, model dependence, and bias" for highly balanced data.

Using the `MatchIt` package (Ho et al., 2022), I performed matching with all the covariates of the adjusted DID model. I first attempted CEM, but it left most units unmatched and resulted in a tiny sample. I then made do with the PSM. I combined exact matching (based on the student's county of residence) and nearest neighbor PSM (based on the other covariates) following the configuration of Bai et al. (2018). Exact matching based on county of residence preserves the original geographic distribution. The propensity score was estimated using a logistic regression of the treatment on the covariates. The matching ratio was set at one treatment unit with up to three control units. The matching produced absolute standardized mean differences below 0.1 for all but a few covariates, suggesting an improved overall balance.

Alike are the results from DID models with matching (DIDM) and those without. In the models of cognitive abilities, I obtained negative, statistically significant coefficients on the treatment variables in the any parent migrated household and only father migrated households. In the models of academic abilities, the treatment variables' coefficients are negative and statistically significant for the any parent migrated households and only mother migrated households. The significance level of any parent migration drops to ten percent. In all models, the magnitudes of the statistically significant coefficients are similar. I present the unadjusted DIDM models below and the adjusted DIDM models in the appendix.

Table 6

Parental migration's effect on children's cognitive test scores, estimated with matching

	Any Parent Migrated	Only Mother Migrated	Only Father Migrated	Both Parents Migrated
Migration	-0.09**	-0.05	-0.13*	-0.05
	(0.03)	(0.06)	(0.06)	(0.11)
W1 score	-0.61***	-0.65***	-0.60***	-0.63***
	(0.03)	(0.04)	(0.04)	(0.06)
Num.Obs.	1958	913	897	475
R2	0.528	0.627	0.638	0.646
R2 Adj.	0.375	0.313	0.320	-0.312
R2 Within	0.363	0.407	0.372	0.351
FE: clsids	X	X	X	X
FE: w2clsids	X	X	X	X

Note: ^^ † $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: ^^ 3:1 nearest neighbor propensity score matching with replacement; exact matching by county

Table 7

Parental migration's effect on children's academic abilities, estimated with matching

	Any Parent Migrated	Only Mother Migrated	Only Father Migrated	Both Parents Migrated
Explanator	-2.65†	-5.34*	-2.42	-2.45
	(1.47)	(2.67)	(2.56)	(3.96)
W1 score	0.03	0.08†	0.05	0.03
	(0.03)	(0.04)	(0.04)	(0.06)
Num.Obs.	1958	913	897	475
R2	0.590	0.682	0.637	0.706
R2 Adj.	0.457	0.413	0.319	-0.087
R2 Within	0.006	0.026	0.008	0.005
FE: clsids	X	X	X	X
FE: w2clsids	X	X	X	X

Note: ^^ † $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: ^^ 3:1 nearest neighbor propensity score matching with replacement; exact matching by county

Discussion

This thesis proposes a model to infer causality between parents' migration and their stay-behind children's educational performance in the short run. I build econometric models in the difference-in-differences design to analyze data from the 2013-2014 and 2014-2015 rounds of China Education Panel Survey. Results suggest that parental migration is, in the short run, negatively associated with children's educational performance as measured by academic exams and standardized cognitive tests. I further examine whether the effect varies across different arrangements of parental migration. Results indicate that father-only migration is negatively associated with children's cognitive abilities, while mother-only migration is negatively associated with children's academic abilities. In all scenarios, the educational performance of newly left-behind children only decreases slightly compared to that of non-left-behind peers.

My research has limitations in sampling due to data constraint. Regarding sample size, the treatment group for the both-parents migration is small (n = 131), making the statistical power low. Regarding identification, I could only identify parental migration through such a condition: parental absence from a household without parental divorce or death. This is because the CEPS questionnaire asked if parents were living in the household, but did not ask why parents were absent. If some parents were jailed or hospitalized, their absence would be wrongly attributed to migration. Besides, I could not control for the migration history of parents, which are not included in the CEPS data. As I previously wrote, some parents out-migrated at an earlier date, returned before the baseline survey, and migrated away again during the survey period. Their children might better cope with parental absence during the survey period, yet they would be mistaken as the newly left-behind . These limitations may bias the estimation.

Limitations also arise from unaccounted endogeneity and exogeneity. As Chen et al. (2009) stated in their research on left-behind children, endogenous factors may create selection bias. When migration opportunities arise, some parents may believe that leaving children behind would hamper children's education, thereby giving up the opportunity. Some other parents may believe that their children's schooling would not suffer from parental absence, thereby embarking on migration. Parental beliefs of this sort are unavailable in CEPS data. Exogenous factors may create omitted variable bias. Suppose that a natural hazard hit many counties of a province in the sample. This shock can simultaneously increase parents' out-migration and reduce stay-behind students' grades (Chen et al., 2009). I could not account for such shocks as CEPS data does not include detailed geographic information.

From my research, we can find new directions for scholarly inquiry. First, when the CEPS team releases the next round of data, researchers can capitalize a the three-wave panel dataset to build multi-period DID models. This would facilitate examination of the parallel trend assumption. Second, researchers can try novel methods. Machine learning, for example, can estimate the heterogeneous effects across subgroups (R. Liu, 2021). Third, researchers can go beyond outbound migration to study return migration of parents (Liang & Li, 2021). Only a few publications have explored return migrants and their stay-behind children in the Chinese context (Démurger & Xu, 2015; Z. Liu et al., 2018).

Let us consider the policy implications for China. The government has enacted reforms in the multilevel citizenship scheme. By 2022, small- and medium-sized cities have liberalized the application for local, urban hukou. However, the most popular migration destinations are metropolises like Beijing and Shanghai. These mega-cities still restrict migrant workers' local citizenship rights (X. Wang, 2020). The hukou scheme shall not remain as it is, despite the small reduction of newly left behind children's schooling performance. The slight reduction is only the short-term consequence. Longer duration of parental migration may hamper educational performance to a greater extent (Liang & Sun, 2020; Meng & Yamauchi, 2017). Besides, educational attainment is only part of human development outcomes. Other outcomes like mental health and non-cognitive skills are also subjected to parental absence's influence (Antia et al., 2020). Policymakers should accelerate the reforms on the multilevel citizenship scheme, opening more doors for parents to migrate together with their children. Schools could dedicate more advisory and counseling support to children who stay behind. "Social workers could test models for training paraprofessionals within different communities" to support left-behind children (M. Wang et al., 2020, p. 1436).

Appendix

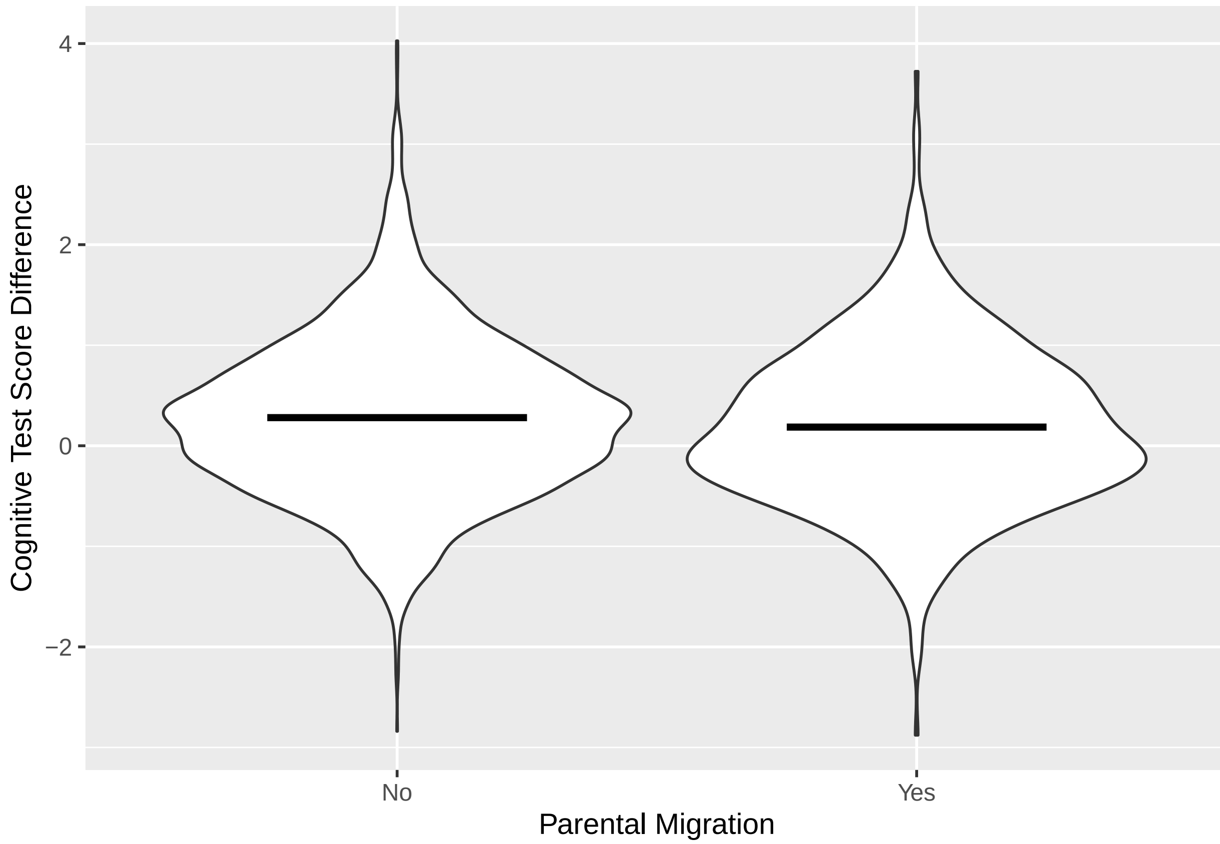

Figure 1

Changes in standardized cognitive test score for new left-behind students and non-left-behind students

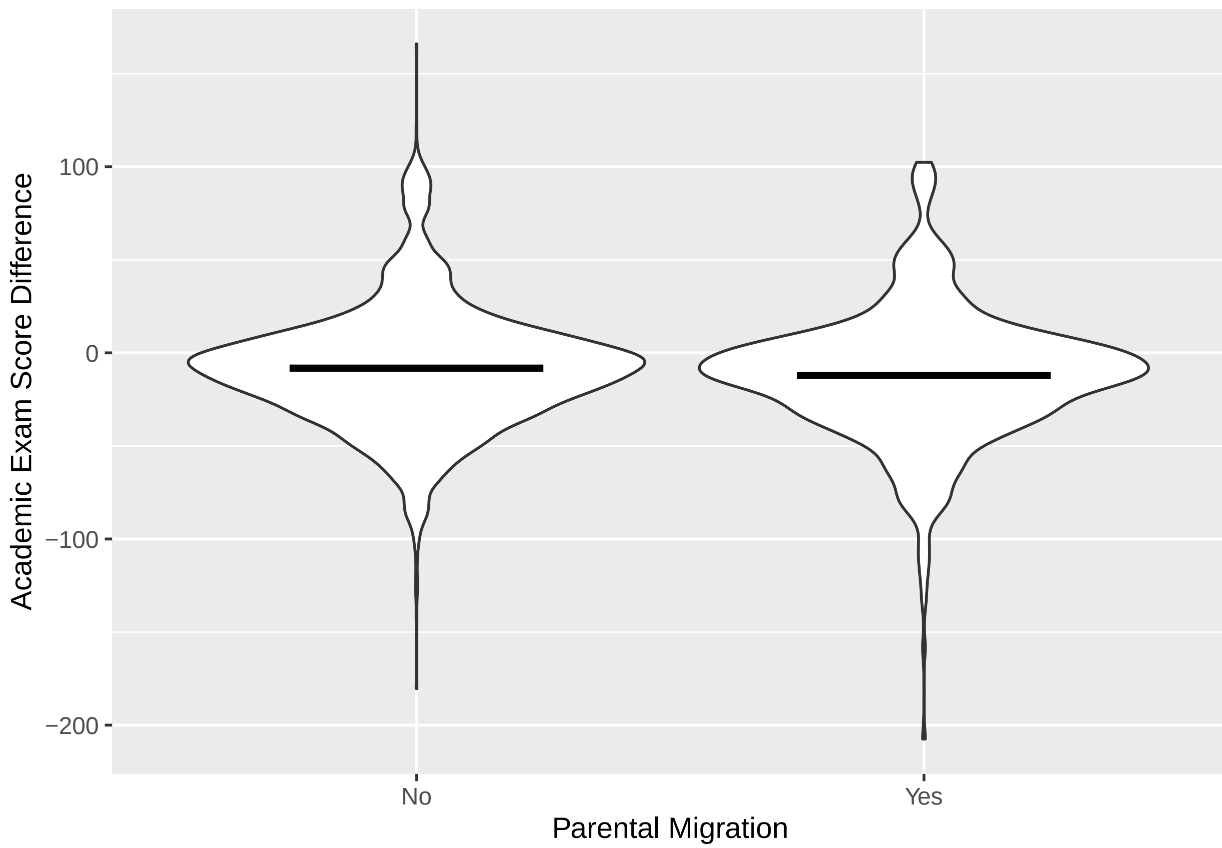

Figure 2

Changes in academic exam score for new left-behind students and non-left-behind students

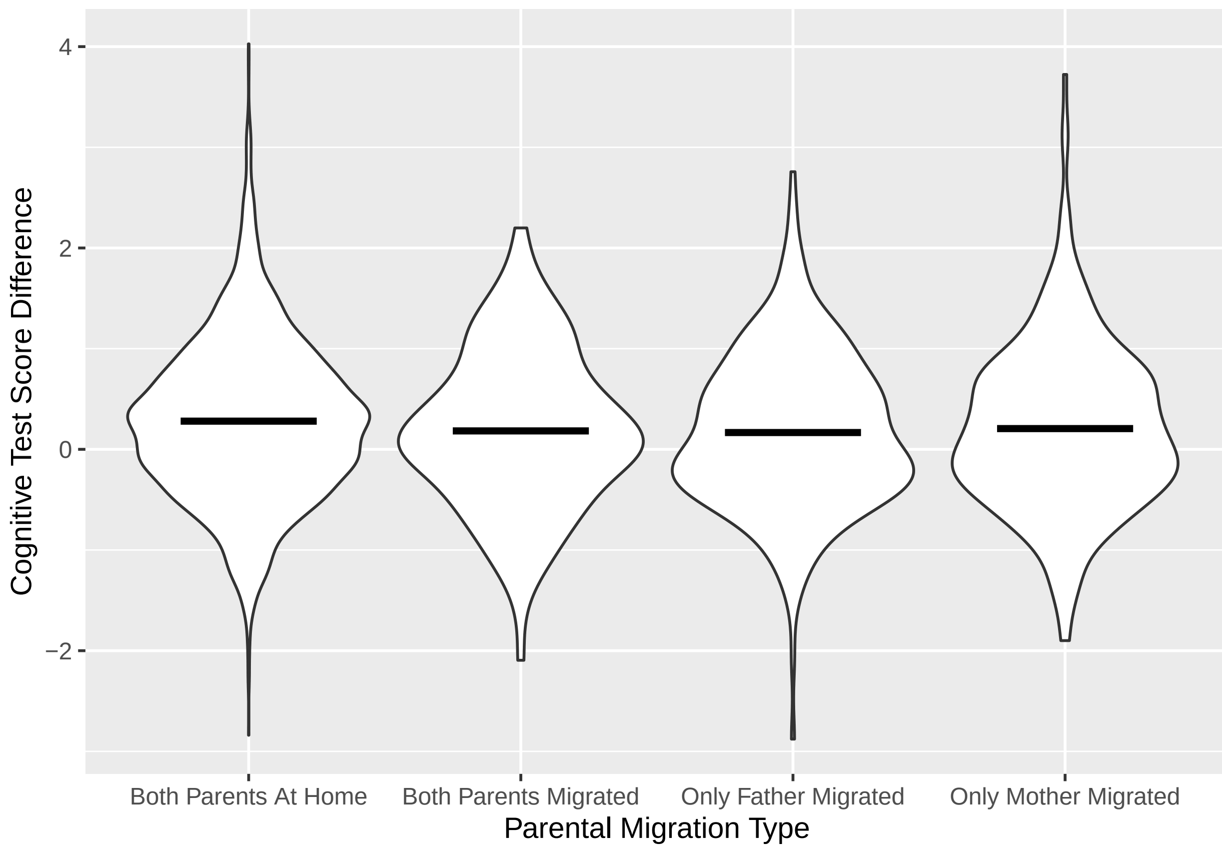

Figure 3

Changes in standardized cognitive test score by household migration arrangement

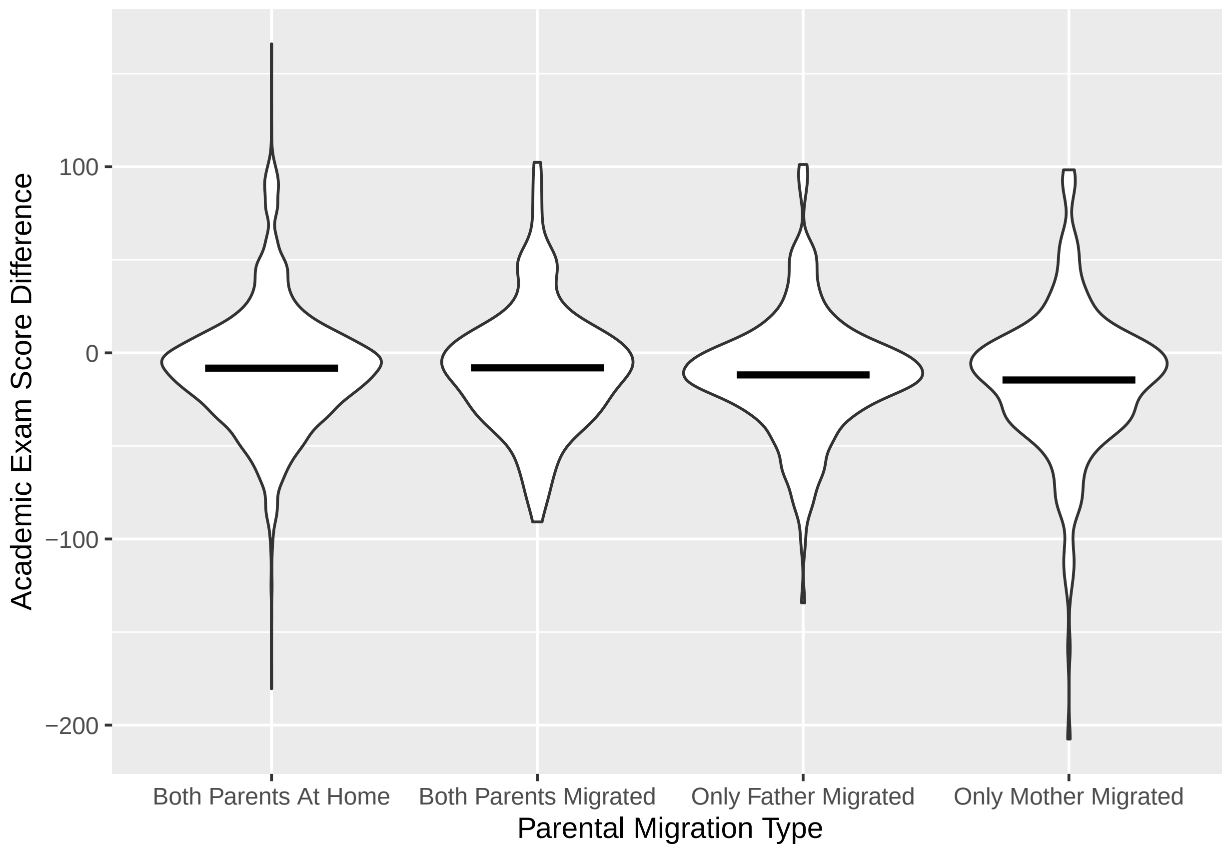

Figure 4

Changes in academic exam score by household migration arrangement

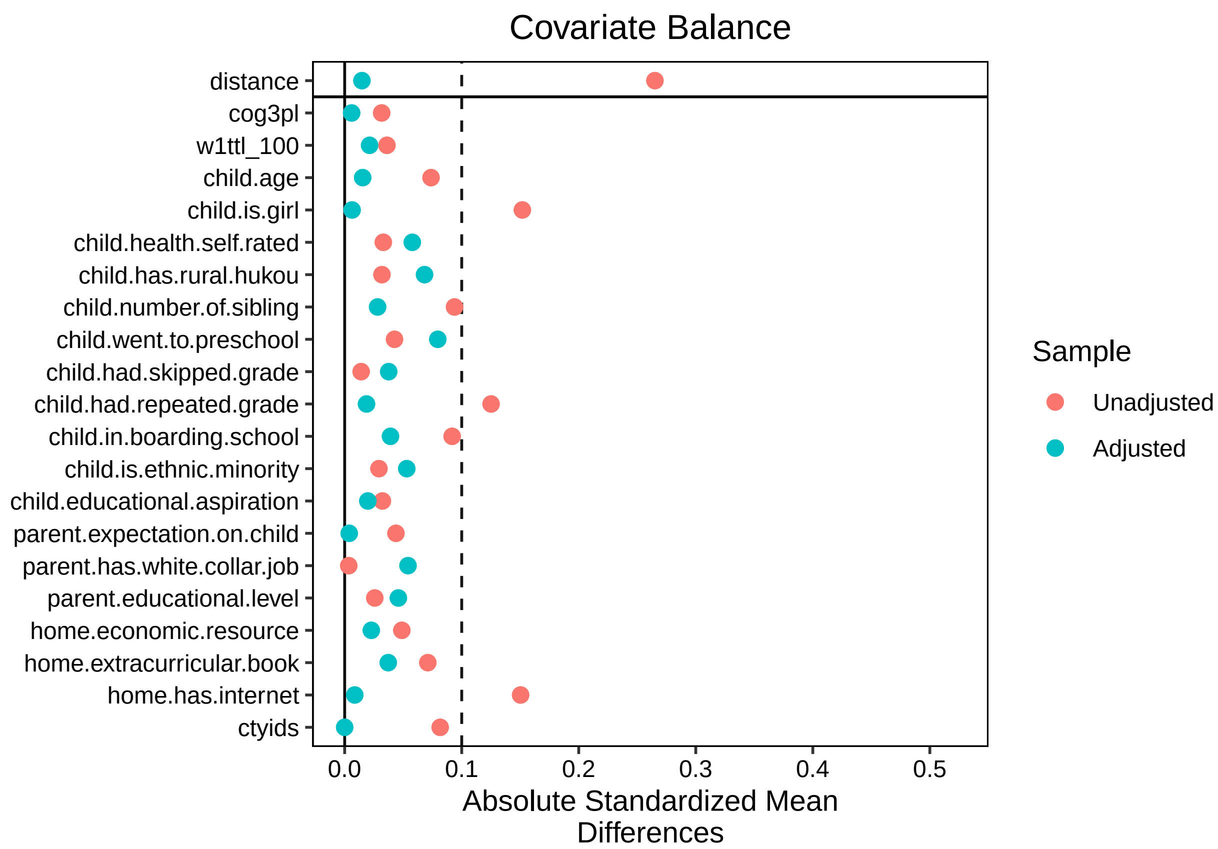

Figure 5

Covariate balance before and after matching by any parent migration

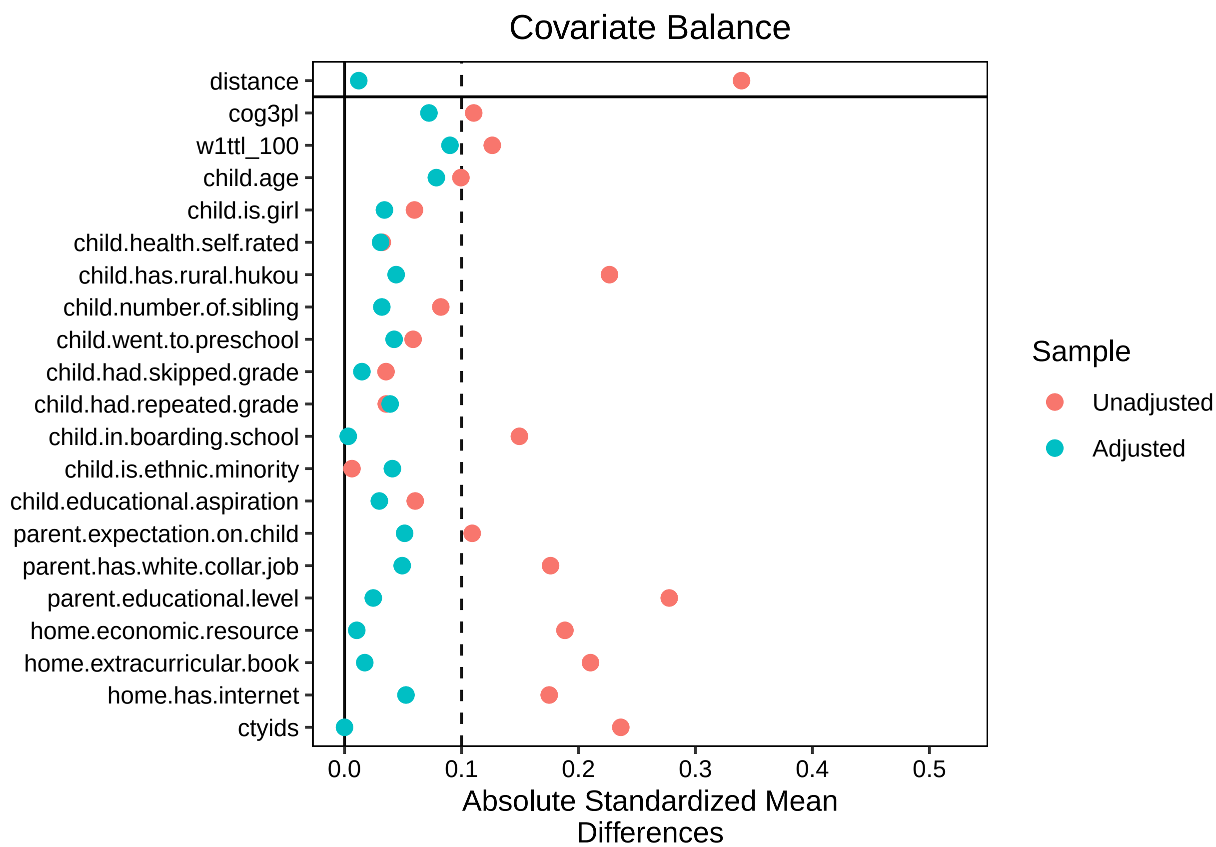

Figure 6

Covariate balance before and after matching by mother-only migration

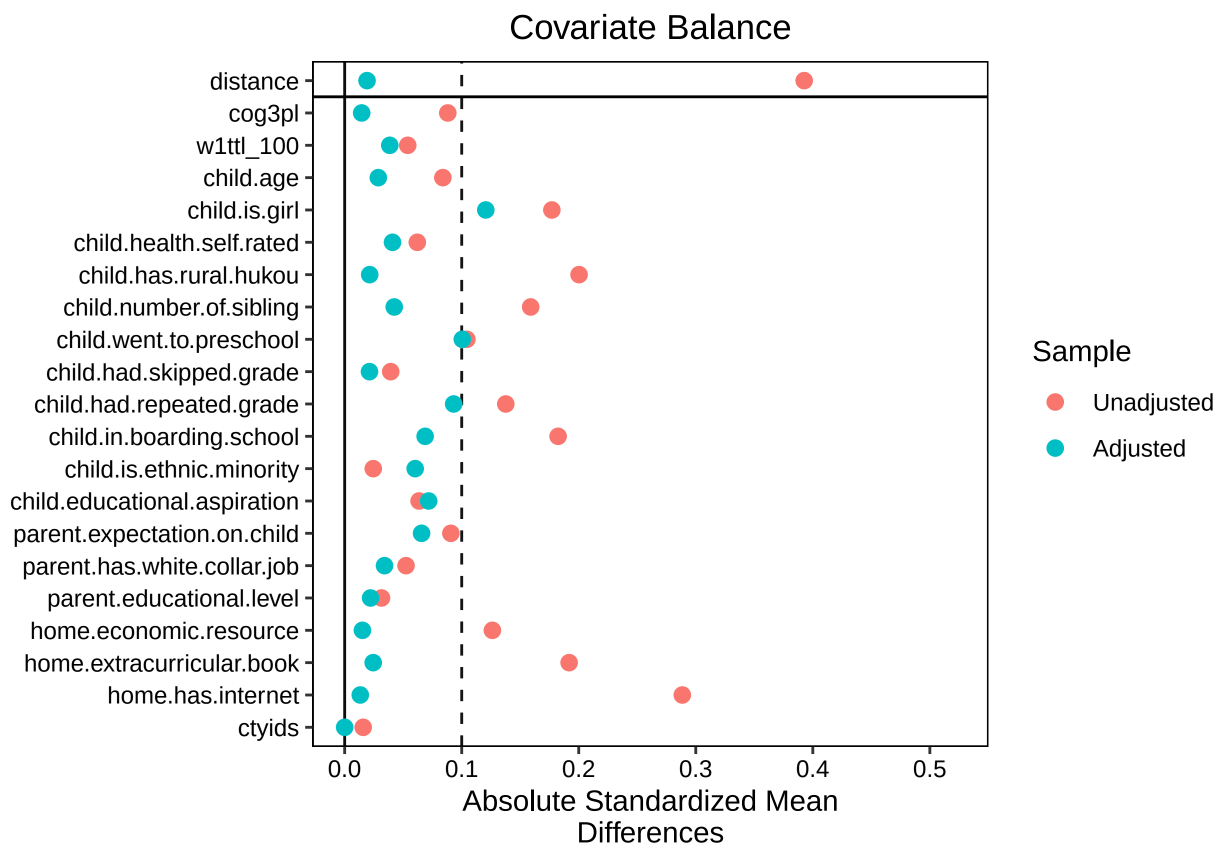

Figure 7

Covariate balance before and after matching by father-only migration

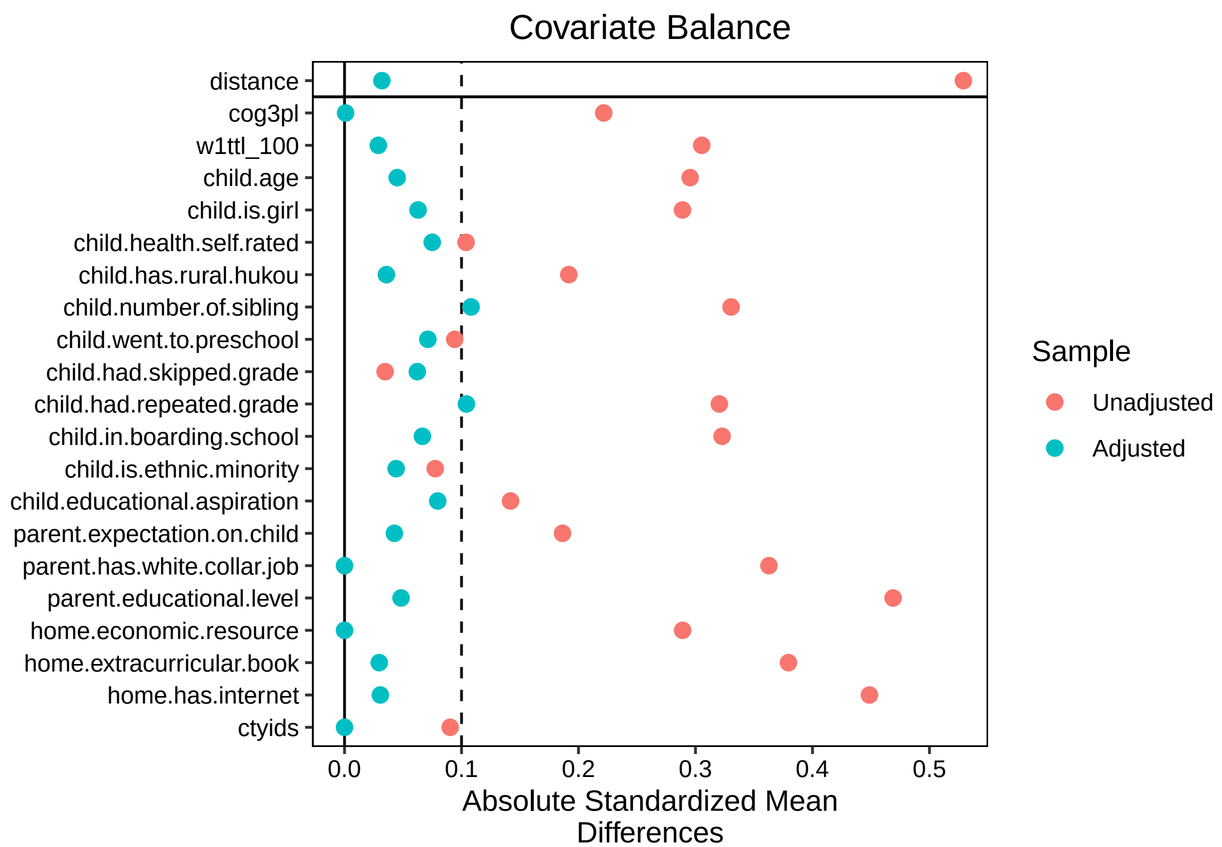

Figure 8

Covariate balance before and after matching by both parents migration

Table 8

Parental migration's effect on children's academic abilities, estimated with matching

	Any Parent Migrated	Only Mother Migrated	Only Father Migrated	Both Parents Migrated
Explanator	-0.09**	-0.04	-0.15*	-0.08
	(0.03)	(0.06)	(0.06)	(0.11)
W1 score	-0.67***	-0.67***	-0.67***	-0.69***
	(0.03)	(0.04)	(0.04)	(0.06)
child.age	-0.08*	-0.02	-0.03	-0.15
	(0.03)	(0.05)	(0.04)	(0.10)
child.is.girl	0.02	0.01	0.05	-0.06
	(0.03)	(0.05)	(0.06)	(0.10)
child.health.self.rated	0.00	-0.03	-0.02	-0.07
	(0.02)	(0.03)	(0.03)	(0.06)
child.has.rural.hukou	0.01	-0.07	0.06	0.04
	(0.04)	(0.07)	(0.07)	(0.12)
child.number.of.sibling	-0.07*	-0.09*	-0.05	-0.10
	(0.03)	(0.04)	(0.04)	(0.07)
child.went.to.preschool	0.04	0.08	0.03	0.30*
	(0.04)	(0.08)	(0.06)	(0.12)
child.had.skipped.grade	-0.08	-0.13	-0.37†	0.34
	(0.16)	(0.24)	(0.19)	(0.45)
child.had.repeated.grade	-0.08	-0.26*	-0.02	0.05
	(0.06)	(0.11)	(0.11)	(0.16)
child.in.boarding.school	0.09	0.15	-0.10	-0.02
	(0.07)	(0.12)	(0.11)	(0.20)
child.educational.aspiration	0.07***	0.03	0.10**	0.10†
	(0.02)	(0.03)	(0.03)	(0.05)
child.is.ethnic.minority	-0.01	0.01	-0.20	0.39
	(0.09)	(0.10)	(0.23)	(0.44)
parent.expectation.on.child	0.07**	0.08†	0.06†	0.01
	(0.03)	(0.05)	(0.03)	(0.06)
parent.has.white.collar.job	0.02	-0.10†	0.03	-0.15
	(0.05)	(0.05)	(0.08)	(0.16)
parent.educational.level	0.01	0.03	0.00	-0.08

	Any Parent Migrated	Only Mother Migrated	Only Father Migrated	Both Parents Migrated
	(0.02)	(0.03)	(0.03)	(0.06)
home.economic.resource	-0.05	0.00	0.02	0.05
	(0.03)	(0.05)	(0.05)	(0.08)
home.extracurricular.book	0.01	0.01	0.02	0.01
	(0.02)	(0.03)	(0.03)	(0.05)
home.has.internet	-0.05	-0.07	-0.06	0.05
	(0.04)	(0.08)	(0.07)	(0.11)
Num.Obs.	1958	913	897	475
R2	0.562	0.653	0.672	0.691
R2 Adj.	0.413	0.337	0.361	-0.318
R2 Within	0.409	0.447	0.431	0.435
FE: clsids	X	X	X	X
FE: w2clsids	X	X	X	X

Note: ^^ † $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: ^^ 3:1 nearest neighbor propensity score matching with replacement; exact matching by county

Table 9

Parental migration's effect on children's academic exam scores, estimated with matching

	Any Parent Migrated	Only Mother Migrated	Only Father Migrated	Both Parents Migrated
Migration	-2.91†	-5.90*	-2.68	-2.94
	(1.48)	(2.64)	(2.56)	(4.21)
W1 score	-0.01	0.01	0.00	-0.03
	(0.03)	(0.04)	(0.05)	(0.06)
child.age	-0.61	1.45	2.59	-2.15
	(1.21)	(2.00)	(1.99)	(3.48)
child.is.girl	4.51**	4.40†	6.58**	3.76
	(1.43)	(2.57)	(2.41)	(4.21)
child.health.self.rated	0.71	2.30	1.13	2.38
	(0.69)	(1.42)	(1.15)	(2.27)
child.has.rural.hukou	0.85	-0.13	-1.10	-2.75
	(1.70)	(3.10)	(2.97)	(4.45)
child.number.of.sibling	1.20	1.92†	1.00	-2.50
	(1.06)	(1.06)	(1.61)	(2.69)
child.went.to.preschool	1.75	-0.30	-2.26	6.39
	(1.76)	(2.47)	(2.57)	(5.13)
child.had.skipped.grade	2.29	-9.76	3.12	32.64
	(6.62)	(11.90)	(12.03)	(29.40)
child.had.repeated.grade	-6.07†	-13.55†	-13.33**	-0.09
	(3.18)	(7.61)	(4.86)	(5.92)
child.in.boarding.school	-0.64	-0.65	-3.42	-3.10
	(3.53)	(5.38)	(4.25)	(8.17)
child.educational.aspiration	1.48†	1.63	0.37	0.44
	(0.86)	(1.06)	(1.20)	(1.92)
child.is.ethnic.minority	3.81	4.84	2.79	-2.54
	(4.31)	(4.68)	(6.53)	(7.64)
parent.expectation.on.child	0.19	1.71	1.41	3.97
	(0.83)	(1.49)	(1.35)	(2.49)
parent.has.white.collar.job	-0.85	0.54	2.13	-1.42
	(1.82)	(2.56)	(2.87)	(6.14)
parent.educational.level	1.30	2.30**	1.91	-2.63

	Any Parent Migrated	Only Mother Migrated	Only Father Migrated	Both Parents Migrated
	(0.97)	(0.85)	(1.41)	(2.54)
home.economic.resource	-0.23	-1.90	-0.51	-0.54
	(1.23)	(2.24)	(1.81)	(4.05)
home.extracurricular.book	-0.66	-0.66	-1.59	0.08
	(0.71)	(1.24)	(1.01)	(1.93)
home.has.internet	-2.89	-1.61	0.08	3.67
	(1.81)	(2.87)	(3.26)	(4.98)
Num.Obs.	1958	913	897	475
R2	0.603	0.702	0.660	0.731
R2 Adj.	0.468	0.431	0.337	-0.150
R2 Within	0.037	0.088	0.070	0.087
FE: clsids	X	X	X	X
FE: w2clsids	X	X	X	X

Note: ^^ † $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: ^^ 3:1 nearest neighbor propensity score matching with replacement; exact matching by county

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