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Impact of Second-Parent Migration on Student Academic Performance in Northwest China and its Implications

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ABSTRACT *The migration of hundreds of millions of rural Chinese workers to the city has contributed substantially to China's economic growth since the beginning of the country's economic reform in 1978. However, this migration has also led to societal issues, including more than 60 million left-behind children. Empirical studies that seek to measure the impact of being left-behind on academic performance have led to inconsistent results, perhaps because the effects may be different for* first-parent *migration (migration during the first period of time in which one parent migrates) and* second-parent *migration (migration when the remaining parent leaves the home). Here we have examined how school performance changes before and after the second parent out-migrates. We use a panel dataset of over 5,000 students from 72 primary schools in rural China. Using a difference-in-difference approach, supported by a placebo test, we find that second-parent migration has statistically significant negative impacts on student performance. Importantly, our data provide convincing evidence that second-parent migration has a more negative impact on academic performance than first-parent migration. Our results have broad implications for China's future economic growth and inequality.*

1. Introduction

While migration from the countryside to the city works through many channels to reduce urban-rural inequality in China, such as by sending remittance income back to the countryside, it has also created a generation of left-behind children (LBCs), who remain in the countryside when their parents migrate (Luo & Yue, 2010; Sicular, Yue, Bjorn, & Li, 2007). This is not a trivial issue. As the number of rural-urban migrant workers has increased, reaching 244 million in 2017, the number of LBCs has also increased, exceeding 60 million in 2010 (ACWF, 2013; NBSC 2018). If parental migration harms the education or human capital formation of LBCs, then it could directly increase educational inequality in the short run and indirectly increase income inequality in the long run (Jeanneney & Hua, 2001; Qian & Smyth, 2008; Sicular et al., 2007).

Does parental migration actually have a negative effect on the education of LBCs? Unfortunately, without careful empirical research, the answer to this question is not clear since theory cannot resolve which of two competing effects is stronger. On the one hand, remittance income could improve

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Dataset and code will be available from the corresponding author upon request.

academic performance by easing liquidity constraints and increasing investment in children and their education (Amuedo-Dorantes & Pozo, 2010; Calero, Bedi, & Sparrow, 2009; Lu, 2012; McKenzie, 2005). On the other hand, parental absence could harm academic performance by decreasing parental care and increasing the domestic and farming responsibilities of LBCs (Chang, Dong, & MacPhail, 2011; de Brauw & Mu, 2011; Lu, 2012; McKenzie, 2005). For example, Chang et al. (2011) finds that parental migration significantly increases the amount of time the children spend on farm and domestic work.

Without clear theoretical predications, any inconsistencies that exist in the empirical literature mean that there may not be a clear conclusion on this important question. Indeed, there are seemingly conflicting findings in the current literature. Some studies, such as Chen, Huang, Rozelle, Shi, and Zhang (2009) and Bai et al. (2018), have found net positive effects of parental migration on the academic performance of LBCs. Both authors found that migration improved academic performance among the students in their sample. Bai et al. (2018) found that the positive effects were especially prominent for poor performing students. Chen et al. (2009) found the largest positive effects for households in which only the father migrated.

In contrast, other research teams have found a net negative effect. For example, both Zhang, Behrman, Fan, Wei, and Zhang (2014) and Zhou, Murphy, and Tao (2014) found significant negative impacts of the migration of both parents on the academic performance of their children. Meng and Yamauchi (2017) examined the cumulative effects of migration and found that exposure to both maternal and paternal migration has negative effects on academic performance. Quantitatively, Zhao, Yu, Wang, and Glauben (2014) found that parental migration can decrease a child's maths score by more than 15 per cent in percentile rankings.

We believe that there are two possible causes of these different findings in the empirical literature. On the one hand, there are a number of methodological (or data-related) shortcomings that might be affecting the nature of these findings. Specifically, many studies, such as Lee (2011), Wang (2014), Zhao et al. (2014), and Zhou et al. (2015), rely on cross-sectional data, which makes it difficult to ascertain causality. Other papers rely on samples that are relatively small in size, such as Lu (2012), Hu (2012), and Lee (2011), all of which used samples of less than 1000 students, which may not provide the adequate statistical power necessary to identify the impact of migration on academic performance. Finally, there also are papers that only collected data from a few towns or a single county (e.g. Zhang et al., 2014). Our sample includes more than 5000 students from 72 schools in rural China over two periods.

On the other hand, it is also possible that the results are inconsistent because the tradeoff between the income and parental care effects is different for *first-parent migration* (migration during the first period of time in which one parent migrates) and *second-parent migration* (migration when the remaining parent leaves the home). To our knowledge, no research team has sought to empirically differentiate the impact of first-parent migration from second-parent migration.

We might expect that the relative strength of the income and parental care effects is different for first-parent migration and second-parent migration for several reasons. First, second-parent migration involves the departure of the final parental caregiver. Zhang et al. (2014) argues that if a single parent is left at home, he or she can largely take on the role of both parents when educating their children. Having no parent at home, however, may have a larger negative impact on the child's education. Zhang et al. (2014), among others, found that grandparents are the primary caregivers for 82 per cent of left-behind children who have two migrant parents, but grandparents tend to have different child-rearing preferences, beliefs, and knowledge than parents do (Wen & Lin, 2012). Further, these households would no longer have a parent around to monitor or help a child with homework, and additional household responsibilities might also fall to the child. Thus, we hypothesise that the negative effect of decreased parental care is greater when the final parent leaves the home than when the first parent out-migrates.

Second, since the family was already receiving remittances from the first parent, we believe that additional remittance income from the second parent's migration would have a smaller marginal impact on educational achievement than the original remittance income from the first parent's migration (Du, Park, & Wang, 2005; Edwards & Ureta, 2003; Taubman, 1989). Jacoby (1994) finds that, while additional income can significantly improve educational outcomes in credit-constrained households, it does not have a significant impact on unconstrained households. Similarly, if the income from the first migrant was already high enough to provide the household with the satisfactory levels of educational support and nutrition that Bai et al. (2018) argues may improve academic performance, then the remittance income from the second migrant will likely have a smaller impact.

For this reason we believe that the nature of migration – that is, whether it is first-parent migration or second-parent migration – has different effects on the academic performance of LBCs. If so, and one set of studies was studying (mostly) first-parent migration, while another set of studies was studying second-parent migration, the literature could be producing what looks like conflicting results when, in fact, there is a perfectly logical consistent explanation.

In this paper we aim to test and examine the consequences of our hypothesis that second-parent migration has a relatively larger negative effect (or less positive effect) on academic performance than does first-parent migration. To meet this goal, we will pursue three specific objectives. First, we compare student achievement across households of different migration status. Second, we move beyond correlation analysis and seek to estimate the causal impact of both first-parent and second-parent migration on academic performance using a difference-in-difference approach, supported by a placebo test. Finally, this paper seeks to understand what types of children (and children from what types of households) are most affected by second-parent migration.

2. Data

A total of 5,104 students from rural Shaanxi Province participated in this study. The study consisted of a baseline and an endline survey, during which we obtained information about the academic performance of the students and the migration status of their parents. In the following subsections, we present the sampling protocol and data collection approach.

2.1. Sampling

Choosing the sample consisted of several steps. First, in order to focus on poor rural areas that likely would have enough variation in household migration status for our analysis, we chose our sample in Ankang Prefecture in Shaanxi Province, a poor area in northwest China. Shaanxi has the second most nationally designated poverty counties among all provinces in China (NBSC, 2013). Ankang Prefecture is one of the poorest areas in the southern part of Shaanxi Province. The average per capita income of the four randomly selected counties was about RMB 5,027 ($817) per year in 2011, below rural China's average per capita income in 2011 of RMB 6,977 (US $1,134 – NBSC, 2012).

Southern Shaanxi is also known as an area of high outmigration (Chan, 2013; Chang, 2014). Low per capita endowments of land in villages characterised by fragile soils and steep gradients give households an extra impetus to seek employment outside of the village. Almost all of the individuals in our sample are Han. Because of this, there are few linguistic (or cultural) barriers to outmigration.

After randomly selecting the counties, in the second step of our sampling process we obtained a comprehensive list of all *wanxiao* (elementary schools with grades one through six) in each of our sample counties. The lists came from each county's local bureau of education. We randomly selected 72 schools in Ankang Prefecture from these lists to be included in our sample. We selected 72 schools in order to be able to generate a sample of around 5,000 students/households – which we considered sufficiently large to generate the power that we would need to undertake this study.

Finally, within the sample schools, we included all third grade and fifth grade students in our baseline survey. We chose third and fifth grade students for several reasons. First, we believe that students in these grades are old enough to fill out their own survey forms and take standardised examinations. Second, we excluded sixth grade students because the study started in June 2011 and extended into the next academic year, at which point the sixth grade students would have already graduated and exited our sample. Finally, we excluded fourth grade students because we believed third and fifth grade students would offer a sharper comparison of the effect of parental migration by age group. Each student in third or fifth grade in our sample schools was included in our baseline sample, giving a total sample size of 5,104 students. Using the baseline data for the necessary parameters, we calculated that the power of this study is 0.75. See Appendix Table 4 in the Supplementary Materials for more details.

Although at the time of baseline survey the sample included 72 schools and 5,104 students, for various reasons (mainly school transfers and extended absences due to illness or injuries) two percent of the original sample attrited by the end of the study. This rate of attrition is quite low compared to other studies conducted with students in rural China and is unlikely to impact our findings (Lai, Luo, Zhang, Huang, & Rozelle, 2015; Mo et al., 2014). We also compared parental migration at baseline for those who attrited versus those who remained in the sample, and found that attrition is not correlated with parental migration status ($p = 0.129$). At the time of the endline survey, we were able to follow up with 5,002 students, who were now in fourth and sixth grade. It is possible that some of the students who did not participate in the endline survey moved to the city to live with a migrant parent. However, we do not focus on this type of migration in this paper, but instead on the students who are left behind in the countryside after their parents migrate.

2.2. Data collection

The research team conducted both rounds of surveying in all 72 sample schools. The baseline survey was conducted in June 2011, at the end of the spring semester. The endline survey was conducted one year later. During each round of the survey, the enumeration team visited each school and conducted a two-part survey.

2.2.1. Academic performance. In the first part of the survey, students were given a 25-minute standardised maths test. We use the scores of this test as our main outcome variable. All questions in the endline test were different from those in the baseline test. Survey enumerators proctored the exams to strictly enforce time limits and prevent cheating.

We use standardised test scores instead of raw test scores to make student performance comparable for different grades, classes, time periods, and cohorts. We standardised each student's test scores relative to the comparison group at the baseline. We standardised the scores separately by grade level.

2.2.2. Parental migration. In the second part of the survey, enumerators collected data on our key independent variable, parental migration status. One section of the questionnaire that the students filled out asked about the migration status of each parent during the current term. Specifically, the questions asked (separately) whether each parent had been away from home for two months or more during the current semester. Migrant workers are officially defined as workers who are 'employed outside their villages and towns for more than six months in the year' (NBSC, 2014). Since a semester is typically around four months long, a migrant worker would thus likely be gone for at least half of those four months. Direct observations and interviews with key informants suggest that most rural labourers, if they are working and living away from home for two months of a semester, are actually away for the entire time.

We examine two main types of households in this study: first-parent migrant households and second-parent migrant households. In first-parent migrant households, the first parent to leave the home does so during the sample period. For our two-period (baseline and endline) sample, this means both parents were home during the baseline survey and exactly one parent outmigrated and was away from home during the endline survey. Therefore, to analyse first-parent migrant households, we restrict our sample to households in which both parents were at home during the baseline survey. Within this sub-sample, the treatment group is made up of the households in which exactly one parent migrated between the baseline and endline surveys (*first-parent migrated households*). The comparison group is made up of households in which neither parent migrated between the baseline and endline surveys (*never migrated households*).

In second-parent migrant households, the remaining parent leaves the home during the sample period. For our sample, this means exactly one parent had outmigrated and was away from home during the baseline survey and both parents were away from home during the endline survey. To analyse second-parent migrant households, we restrict our sample to the households in which exactly one parent was away from home during the baseline survey. Within this sub-sample, we then define the treatment group as households in which both parents were away from home at the time of the endline survey (*both parents migrated households*). The comparison group in the second-parent sample is made up of households in which exactly one parent was away from home during the baseline and exactly one parent was away from home during the endline as well (*single-parent migrated households*). Additionally, we required that the parent who was away from home during the endline was the same parent who was away from home during the baseline.

To examine first-parent migration in the sample we collected, we restrict our sample to the 2,051 households (40.9% of the total sample) in which both parents stayed at home in the baseline survey (Table 1, columns 3, 5, 8, row 4). The 471 households (21.3% of the first-parent sample) in which the first and only parent to leave the home does so between baseline and endline surveys (Table 1, columns 3, 5, row 4) are the treatment group (*first-parent migrated households*). In contrast, the 1,580 households (71.5% of the first-parent sample) in which neither the father nor the mother migrated during either the baseline or endline surveys (column 8, row 4) make up the comparison group (*never migrated households*).

For second-parent migration, the 222 households in which exactly one parent migrated in 2011 but both parents migrated in 2012 (column 7, rows 1–2) make up our treatment group (*both parents migrated households*). The 948 households in which only the father migrated in both 2011 and 2012 (column 3, row 1) and the 164 households in which only the mother migrated in both 2011 and 2012 (column 5, row 2) together make up our comparison group (*single-parent migrated households*).

2.2.3. Other covariates. In the second part of the survey the enumerators also collected data on the characteristics of students and their families. We created demographic and socioeconomic variables based on this part of the survey. The dataset includes measures of each student's characteristics, including *gender, age, ethnicity, grade, boarding student, repeated a grade*, and *oldest child*. We also created a number of variables that measure family characteristics, including *assets, father has at least a junior high school degree, mother has at least a junior high school degree, number of siblings*, and *family member helps with schoolwork* (Tables 2 and 3). While most of these variables were taken directly from the questionnaire responses, the *assets* variable was calculated by multiplying the quantity of each durable good owned by its price, then summing over all goods and taking the logarithm. The data that were used to create these covariates were collected at the baseline survey (before the migration event), so we will control for these additional covariates to compare households that were similar to each other prior to migration, and more efficiently measure the effect of migration on academic performance. Since we cannot control for changes in household income or assets between the baseline and endline, our estimated effect combines the negative effect of decreased parental care and the positive effect of increased income. Certain additional variables also allow us to explore whether migration has heterogeneous effects on academic performance across children and households.

Table 1. Patterns of migration in sample households in June 2011 and June 2012, Shaanxi Province, China

Migration status in June 2011	Migration status in June 2012							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Number of households in 2011	Any Parent Migrated in 2012	Only Father Migrated in 2012	Father Migrated in 2012	Only Mother Migrated in 2012	Mother Migrated in 2012	Both Parents Migrated in 2012	Neither parent migrated in 2012
[1] Father migrated only	1543	1145	948	1116	29	197	168	398
[2] Mother migrated only	336	248	30	84	164	218	54	88
[3] Both parents migrated	914	784	182	730	54	602	548	130
[4] Neither parent migrated	2209	629	387	545	84	242	158	1580
[5] Total number of households	5002	2806	1547	2475	331	1259	928	2196

Source: Authors' survey.
Column (1) = Column (3) + Column (5) + Column (7) + Column (8);
Column (2) = Column (3) + Column (5) + Column (7);
Column (4) = Column (3) + Column (7);
Column (6) = Column (5) + Column (7).
The households in column 8, rows 1, 2 and 3 are 'return migrants' (households that had a migrant in 2011 who returned home in 2012). These households are dropped from the multivariate analysis.
The households in rows 1–3, columns 2–7 are 'always migrant' households.
Total 'new migrants' (those households in which neither parents migrated in 2011 but at least one migrated in 2012) are found in column 2, row 4.
'Never migrants' are found in column 8, row 4.

Table 2. Descriptive statistics of control variables used in the first-parent multivariate analysis

Control variables	Total Mean (s.d.) (1)	No parents migrated Mean (s.d.) (2)	One parent migrated Mean (s.d.) (3)	H0: (2) = (3) Difference Mean (s.e.) (4)
Characteristics of the students				
[1] Female (1 = female; 0 = male)	0.49	0.49	0.46	−0.03
	(0.50)	(0.50)	(0.50)	(0.03)
[2] Age (years)	11.66	11.67	11.62	−0.05
	(1.30)	(1.30)	(1.32)	(0.07)
[3] Ethnic minority (1 = yes; 0 = no)	0.02	0.02	0.01	−0.01
	(0.13)	(0.14)	(0.09)	(0.01)
[4] 5th grade (1 = yes; 0 = no)	0.52	0.53	0.46	−0.07***
	(0.50)	(0.50)	(0.50)	(0.03)
[5] Boarding student (1 = yes; 0 = no)	0.46	0.45	0.49	0.03
	(0.50)	(0.50)	(0.50)	(0.03)
[6] Repeated a grade (1 = yes; 0 = no)	0.30	0.29	0.34	0.05**
	(0.46)	(0.45)	(0.47)	(0.02)
[7] Oldest child (1 = yes; 0 = no)	0.57	0.56	0.61	0.04*
	(0.49)	(0.50)	(0.49)	(0.03)
Characteristics of the parents and the households				
[8] Log (asset)	9.18	9.20	9.11	−0.08
	(1.20)	(1.19)	(1.24)	(0.06)
[9] Father has at least junior high	0.54	0.56	0.50	−0.06**
School degree (1 = yes; 0 = no)	(0.50)	(0.50)	(0.50)	(0.03)
[10] Mother has at least junior high	0.35	0.36	0.31	−0.05**
School degree (1 = yes; 0 = no)	(0.48)	(0.48)	(0.46)	(0.03)
[11] Number of siblings	1.01	0.99	1.09	0.11**
	(1.03)	(0.98)	(1.15)	(0.05)
[12] Family member helps with	0.92	0.92	0.91	0.00
Schoolwork (1 = yes; 0 = no)	(0.28)	(0.28)	(0.28)	(0.01)
[13] Attrition				
[14] Observations	2,051	1,580	471	2,051

Source: Author's survey.
Notes: *Significant at 10%, **significant at 5%, ***significant at 1%.

2.3. Correlation between migration and academic performance: descriptive results

In this section we compare the distribution of the scores of students across households of different migration status. We first provided a detailed description of the different types of migrant households and described their prevalence. Now, we present correlations between migration status and academic performance by comparing changes in academic performance between periods with changes in migration status.

For first-parent migrant households, the descriptive results suggest that changes in scores of students in the treatment group, *first-parent migrated households*, were the same as of students in the control group, *never migrated households*. For the comparison group, the mean of standardised maths test scores was 0 at the baseline survey and −1.26 at the endline survey (Table 4, columns 1–2, row 1). Note, because we standardised test scores relative to the comparison group at the baseline survey, the comparison group has a mean of zero in the baseline time period by construction. For the

Table 3. Descriptive statistics of control variables used in the second-parent multivariate analysis

Control variables	Total	One parent migrated	Both parents migrated	H0: (2) = (3) Difference
	Mean (s.d.) (1)	Mean (s.d.) (2)	Mean (s.d.) (3)	Mean (s.e.) (4)
Characteristics of the students				
[1] Female (1 = female; 0 = male)	0.48	0.48	0.50	0.02
	(0.50)	(0.50)	(0.50)	(0.04)
[2] Age (years)	11.70	11.71	11.60	−0.11
	(1.28)	(1.27)	(1.36)	(0.09)
[3] Ethnic minority (1 = yes; 0 = no)	0.00	0.00	0.00	0.00
	(0.05)	(0.04)	(0.07)	(0.00)
[4] 5th grade (1 = yes; 0 = no)	0.54	0.56	0.45	−0.11***
	(0.50)	(0.50)	(0.50)	(0.04)
[5] Boarding student (1 = yes; 0 = no)	0.41	0.40	0.44	0.04
	(0.49)	(0.49)	(0.50)	(0.04)
[6] Repeated a grade (1 = yes; 0 = no)	0.33	0.32	0.36	0.04
	(0.47)	(0.47)	(0.48)	(0.03)
[7] Oldest child (1 = yes; 0 = no)	0.57	0.58	0.56	−0.01
	(0.49)	(0.49)	(0.50)	(0.04)
Characteristics of the parents and the households				
[8] Log (asset)	9.16	9.14	9.23	0.09
	(0.86)	(0.91)	(0.54)	(0.06)
[9] Father has at least junior high	0.51	0.50	0.53	0.03
School degree (1 = yes; 0 = no)	(0.50)	(0.50)	(0.50)	(0.04)
[10] Mother has at least junior high	0.30	0.30	0.31	0.01
School degree (1 = yes; 0 = no)	(0.46)	(0.46)	(0.46)	(0.03)
[11] Number of siblings	1.04	1.04	1.04	0.01
	(1.15)	(1.18)	(1.00)	(0.08)
[12] Family member helps with	0.91	0.91	0.91	0.00
Schoolwork (1 = yes; 0 = no)	(0.28)	(0.28)	(0.29)	(0.02)
[13] Attrition				
[14] Observations	1334	1112	222	1334

Source: Author's survey.
Notes: *Significant at 10%, **significant at 5%, ***significant at 1%.

treatment group, the mean score at the time of the baseline survey was −0.05 SD (column 1, row 2). By the endline survey, the average scores of students in the treatment group decreased by 1.26 SD to −1.31 (column 2, row 2). This means that the scores of students in the treatment group did not decrease more between the baseline and endline surveys than did the scores of students in the comparison group (column 3, row 3).

For second-parent migration, *both parents migrated households* are the treatment group and *single-parent migrated households* are the comparison group. As before, the mean standardised test score for the comparison group was 0 at the baseline survey, and the mean standardised test score decreased to −1.29 SD by the time of the endline survey (Table 4, columns 1–2, row 4). For the treatment group, the mean score at the time of the baseline survey was −0.20 SD (Table 4, column 1, row 5). By the endline survey, the average scores of students in the treatment group decreased by 1.24 SD to −1.44 SD (column 2, row 5). This means that the scores of students in the treatment group decreased by 0.05 SD less between the baseline and endline surveys than did the scores of students in the

Table 4. Change in standardised maths test scores of students before and after parental migration for both treatment and comparison groups

	Standardised maths test scores of students			
	Baseline (1)	Endline (2)	Difference (3)	P-value (4)
	Mean (se)	Mean (se)	Mean (se)	H0: (1) = (2)
First-parent migration				
[1] Comparison group	0	−1.26	−1.26	
	(0.03)	(0.02)	(0.02)	
[2] Treatment group	−0.05	−1.31	−1.26	
	(0.05)	(0.05)	(0.04)	
[3] Difference	−0.05	−0.05	0	
	(0.05)	(0.04)	(0.04)	**0.90**
Second-parent migration				
[4] Comparison group	0	−1.29	−1.29	
	(0.03)	(0.02)	(0.03)	
[5] Treatment group	−0.20	−1.44	−1.24	
	(0.07)	(0.05)	(0.06)	
[6] Difference	−0.20	−0.15	0.05	
	(0.07)	(0.05)	(0.07)	**0.48**

Source: Author's survey.
Note: P-values are for the significance of the difference in differences (bolded).

comparison group (column 3, row 6). However, these results are, again, not statistically significant (column 4, row 6).

These findings, that both first-parent and second-parent migration have insignificant effects on student academic achievement, are consistent with Zhou et al. (2015) and Lu (2012), who found no significant relationship between parental migration and academic performance. However, in this section we did not control for other variables. Adding control variables will allow us to increase efficiency and better understand the ceteris paribus effect of migration on academic performance. We do so in the Multivariate Analysis section.

3. Methodology for the multivariate analysis

In this section we explain the difference-in-difference approach that we use to further examine how first-parent and second-parent migration affects the educational performance of LBCs. We also explain our use of a placebo test to verify the parallel-trend assumption underlying the validity of the difference-in-difference approach.

3.1. Difference-in-difference approach

We use a Difference-in-Difference (hereafter, DD) approach to compare how academic performance changes before and after students' parent(s) out-migrated relative to students in the comparison group. This comparison produces the standard DD estimator. In the first specification of our model, we use an *unrestricted and unadjusted* model:

$$\Delta Score_{is} = \alpha + \beta \cdot MIG_{is} + \delta \cdot Score_{is,baseline} + \lambda \cdot S_s + \varepsilon_{is} \tag{1}$$

where i denotes student i in school s and $\Delta Score_{is}$ is the change in standardised maths test score of student i in school s between the baseline and endline surveys. MIG_{is} is a dummy for parental migration status, the treatment variable, which makes β the parameter of interest. The school effect is captured by λ. $Score_{is,\ baseline}$ represents the standardised baseline maths test score of student i in school s. Note that we call this model unrestricted because this model does not imply a restriction on the coefficient associated with baseline grades. We call the model unadjusted because it does not adjust for additional covariates.

In addition to the *unrestricted and unadjusted* DD estimator, we implement one other DD estimator: an 'adjusted' version of the model that includes a series of control variables from the baseline survey in addition to the treatment variable *(unrestricted and adjusted)*. The unrestricted and adjusted DD estimators relax the implicit restrictions in the unrestricted and unadjusted DD estimator that the coefficient associated with covariates gathered from the baseline survey equals one. The unrestricted and adjusted model is:

$$\Delta Score_{is} = \alpha + \beta \cdot MIG_{is} + \delta \cdot Score_{is,baseline} + \gamma \cdot X_{is} + \lambda \cdot S_s + \varepsilon_{is} \qquad (2)$$

where the term X_{is} is a vector of covariates collected at the baseline survey that are included to capture the characteristics of students, their parents and households.

We also use a version of Equation (2) to test for the heterogeneous effects of second-parent migration on the educational performance of the sample students. We do this by including an interaction term between the treatment dummy variable and variables that may potentially heterogeneously affect the outcome through the treatment. The model to test this is:

$$\Delta Score_{is} = \alpha + \beta_1 \cdot MIG_{is} + \beta_2 \cdot D_{is} + \beta_3 \cdot MIG_{is} \cdot D_{is} + \delta \cdot Score_{0is} + \gamma \cdot X_{is} + \lambda \cdot S_s + \varepsilon_{is} \qquad (3)$$

where the coefficient on the interaction term, β_3, indicates the heterogeneous treatment effect.

In all of the regressions, we accounted for the clustered design by constructing Huber-White standard errors clustered at the school level (relaxing the assumption that disturbance terms are independent and identically distributed within schools).

3.2. Placebo test

The identification of causal effects using DD relies on the assumption that without the treatment, the average change in the outcomes of the treatment and comparison groups would be the same. Formally, this is called the *parallel trend assumption*. However, it is possible that even without the treatment, the treatment and comparison groups would have behaved differently because of something fundamentally different about the behaviour of households/individuals within each of the groups. If that is the case, and the parallel trend assumption does not hold, then the DD results might be biased.

To test whether the parallel assumption holds, we perform a *placebo test* using data from a period prior to when the treatment took place. Specifically, following the check proposed by Duflo (2003), we use a DD approach to test whether the outcomes of the treatment and comparison groups move in parallel in the period prior to the treatment.

To implement the placebo test in our sample, we use data provided by the same research group that conducted our baseline and endline surveys. This group conducted a pre-baseline survey with all the third and fifth grade students in our 72 sample schools in late February 2011, before the baseline survey was administered. To conduct the placebo test, we redo the DD analysis comparing score changes between the pre-baseline and baseline periods for students in the treatment and comparison groups of the second-parent migration sample. These treatment and comparison groups are the same second-parent migration treatment and comparison groups defined earlier in the text. While these groups are defined by their migration status at the baseline and endline surveys, in the placebo test we examine how their scores changed between the pre-baseline and baseline surveys. Since the parents of students in the treatment group migrated between the baseline and endline surveys, after the period analysed in the placebo test, we hope that the treatment and comparison groups moved in parallel between the pre-baseline and baseline surveys.

3.3. Other approaches

Many factors could lead to migration, and some of these factors could also be correlated with the child's well-being or academic performance. While with cross-sectional data we would not be able to comprehensively control for all of these factors without using an instrumental variable, using the DD approach with our panel data controls for all time-invariant factors.

Although DD controls for time-invariant differences between groups, it does not control for time-varying endogeneity, such as shocks that cause both migration and a change in academic performance. Although the migration literature has historically used instrumental variables in response to concerns about time-varying endogeneity, we do not believe an instrumental variables approach is appropriate for our study. McKenzie and Rapoport (2011) note that with instrumental variables, 'while the impact of migration is likely to vary with the type of migration, we can at best identify the average affect.' Since we specifically want to investigate the impact of a certain type of migration (second-parent migration) and do not want the average effect, instrumental variables traditionally used in the migration literature that estimate the average effect of migration, such as the presence of migrant networks, weather shocks, or distance to the destination city, would not be appropriate for our application (McKenzie & Rapoport, 2011; Meng & Yamauchi, 2017). We encourage further research into second-parent migration to determine correlates of second-parent migration among households where the first parent has already migrated, which could be used to develop an instrument that accurately captures the effect of second-parent migration.

4. Results of multivariate analysis

4.1. Effects of parental migration on educational performance

4.1.1. Results from DD analysis. For first-parent migration, we use models (1) – (2) of the DD estimator to examine the effect of migration on academic performance in migrant households. One of the most important findings from Table 5 is that first-parent migration does not significantly affect school performance. In both models, the coefficient of the *first-parent migrated households* dummy variable is negative but not statistically significant. This means that, everything else held constant, after the first parent in a household out-migrated between baseline and endline surveys, the migration did not cause a significant decrease in their child's standardised maths test scores.

For second-parent migration, the results from the DD analysis using models (1) – (2) are consistent with our hypothesis that second-parent migration has a relatively larger negative effect on school performance than first-parent migration. For example, when we use the unrestricted and adjusted specification of the DD estimator (Table 6, column 2), the coefficient of the *both parents migrated households* dummy variable is −0.08 SD and statistically significant (at the 10% level). This means that, everything else held constant, after the remaining parent in a household out-migrated between baseline and endline surveys, their child's standardised maths test scores decreased relative to the children of *single-parent migrated households*. A Wald test also shows that this coefficient is significantly larger than the estimated coefficient of MIGi in Table 5 (significant at 1%). In the rest of paper, we focus mainly on the results from the unrestricted and adjusted model, which best fits the data (has the highest adjusted R-squared statistic) since it captures baseline scores as well as other covariates.

Table 5. Difference in difference regression results analysing the effects of first-parent migration on academic performance, Shaanxi Province, China

Dependent variable: $\Delta Score_i = Score_{i,\ 2012}\text{-}Score_{i,\ 2011}$	Unrestricted & unadjusted	Unrestricted & adjusted
Variables	(1)	(2)
Treatment variable (MIG_i)		
[1] First Parent Migrated (1 = yes; 0 = no)	−0.02	−0.01
	(0.03)	(0.03)
Characteristics of the students		
[2] Female (1 = female; 0 = male)		−0.00
		(0.02)
[3] Age (years)		−0.08***
		(0.02)
[4] 5th grade (1 = yes; 0 = no)		0.08
		(0.05)
[5] Is an ethnic minority (1 = yes; 0 = no)		0.14
		(0.09)
[6] Boarding student (1 = yes; 0 = no)		−0.05*
		(0.03)
[7] Has ever repeated a grade (1 = yes; 0 = no)		−0.05*
		(0.03)
[8] Is the oldest child (1 = yes;0 = no)		−0.00
		(0.03)
[9] Log (asset)		0.01
		(0.01)
[10] Father has at least junior high		0.02
School degree (1 = yes; 0 = no)		(0.03)
[11] Mother has at least junior		0.04*
High school degree (1 = yes; 0 = no)		(0.03)
[12] Number of siblings		−0.03*
		(0.02)
[13] Family member assists with homework		0.06
(1 = yes; 0 = no)		(0.05)
[14] Standardised pre Maths test score	−0.64***	−0.67***
(standard deviation)	(0.02)	(0.02)
[15] School dummy	YES	YES
[16] Constant	−1.59***	−0.87***
	(0.01)	(0.23)
[17] Number of observations	2,051	2,051
[18] R-squared	0.58	0.59

Source: Author's survey.
Notes: In this specification, our sample is households in which neither parent migrated in June 2011. Our treatment group is households in which exactly one parent migrated in 2012, and our comparison group is households in which neither parent migrated in 2012. *Significant at 10%, **significant at 5%, ***significant at 1%.

4.1.2. Validity of the parallel trend assumption. Results from the placebo test demonstrate that the parallel trend assumption appears to be valid in our sample. Specifically, when we compare the change in standardised maths test scores of students between the pre-baseline and baseline periods, the coefficients on the migration variable for the unrestricted and adjusted DD estimator model is not significantly different from zero (Table 7, column 2, row 1). In other words, the scores of our treatment group (*both parents migrated*) and comparison group (*single parent migrated*) seem to be tracking one another fairly closely before the migration occurs. Therefore, it is fair for us to say that the results in the following DD analysis are accurate, given that there is no evidence that the parallel trend assumption is violated.

Table 6. Difference in difference regression results analysing the effects of second-parent migration on academic performance, Shaanxi Province, China

Dependent variable: $\Delta Score_i = Score_{i,\ 2012}\text{-}Score_{i,\ 2011}$	Unrestricted & unadjusted	Unrestricted & adjusted
Variables	(1)	(2)
Treatment variable (MIG_i)		
[1] Both Parents Migrated (1 = yes; 0 = no)	−0.08*	−0.08*
	(0.05)	(0.05)
Characteristics of the students		
[2] Female (1 = female; 0 = male)		−0.04
		(0.03)
[3] Age (years)		−0.03
		(0.03)
[4] 5th grade (1 = yes; 0 = no)		0.06
		(0.07)
[5] Is an ethnic minority (1 = yes; 0 = no)		0.09
		(0.26)
[6] Boarding student (1 = yes; 0 = no)		−0.10**
		(0.04)
[7] Has ever repeated a grade (1 = yes; 0 = no)		−0.15***
		(0.04)
[8] Is the oldest child (1 = yes;0 = no)		−0.03
		(0.03)
[9] Log (asset)		0.03
		(0.02)
[10] Father has at least junior high		−0.01
School degree (1 = yes; 0 = no)		(0.03)
[11] Mother has at least junior		0.02
High school degree (1 = yes; 0 = no)		(0.03)
[12] Number of siblings		−0.03**
		(0.02)
[13] Family member assists with homework		−0.04
(1 = yes; 0 = no)		(0.06)
[14] Standardised pre Maths test score	−0.69***	−0.70***
(standard deviation)	(0.02)	(0.02)
[15] School dummy	YES	YES
[16] Constant	−1.68***	−1.34***
	(0.02)	(0.33)
[17] Number of observations	1,334	1,334
[18] R-squared	0.60	0.61

Source: Author's survey.
Notes: In this specification, our sample is households with exactly one migrant parent at the baseline. Our treatment group (MIG = 1) is households with two migrant parents at the endline, and our comparison group (MIG = 0) is households whose migration status is the same as at the baseline. Wald test also shows the coefficient of MIG_i (−0.08) is significantly greater than the coefficient of MIG_i (−0.01) in Table 5 (significant at 1%). *Significant at 10%, **significant at 5%, ***significant at 1%.

4.2. Heterogeneous effects of second-parent migration on educational performance

While we found negative impacts of second-parent migration on the academic performance of LBCs, these results have all been for the average household. It is possible that the impacts could vary for different subgroups. We use model (3) to test for heterogeneity in the effects of second-parent migration across subgroups. This analysis shows that the negative effect on LBCs is greater for oldest children and non-boarding students. See Supplementary Materials for more details.

Table 7. Placebo test results for second-parent migration, Shaanxi Province, China

Dependent variable: $\Delta Score_i = Score_{i,\ June\ 2011}$-$Score_{i,\ February\ 2011}$	Unrestricted & unadjusted	Unrestricted & adjusted
Variables	(1)	(2)
Treatment variable (MIG$_i$)		
[1] Both Parents Migrated in 2012 (1 = yes; 0 = no)	−0.16*	−0.06
	(0.06)	(0.06)
Characteristics of the students		
[2] Female (1 = female; 0 = male)		0.04
		(0.04)
[3] Age (years)		−0.10*
		(0.05)
[4] 5th grade (1 = yes; 0 = no)		1.08***
		(0.13)
[5] Is an ethnic minority (1 = yes; 0 = no)		0.25
		(0.57)
[6] Boarding student (1 = yes; 0 = no)		0.09
		(0.06)
[7] Has ever repeated a grade (1 = yes; 0 = no)		0.01
		(0.06)
[8] Is the oldest child (1 = yes;0 = no)		0.06
		(0.06)
[9] Log (asset)		−0.01
		(0.02)
[10] Father has at least junior high School degree (1 = yes; 0 = no)		0.06
		(0.05)
[11] Mother has at least junior High school degree (1 = yes; 0 = no)		0.00
		(0.06)
[12] Number of siblings		−0.03
		(0.03)
[13] Family member assists with homework (1 = yes; 0 = no)		0.01
		(0.10)
[14] Standardised pre Maths test score (standard deviation)	−0.40***	−0.43***
	(0.04)	(0.04)
[15] School dummy	YES	YES
[16] Constant	−0.23***	0.30
	(0.03)	(0.58)
[17] Number of observations	1,334	1,334
[18] R-squared	0.22	0.38

Source: Author's survey.
Notes: In this specification, our sample is households with exactly one migrant parent at the baseline. Our treatment group (MIG = 1) is households with two migrant parents at the endline, and our comparison group (MIG = 0) is households whose migration status is the same as at the baseline. *Significant at 10%, **significant at 5%, ***significant at 1%.

As an additional test of how the effects of first and second-parent migration differentially effect academic performance, we examine the data set used by Bai et al. (2018). See Supplementary Materials for more details.

4.3. Discussion

Why is it that first-parent migration does not have a significant negative effect on the scores of migrant children while second-parent migration has a statistically significant negative effect on students' scores? One possible reason is that the tradeoff between the income and parental effects is different for first-parent migration and second-parent migration. This may occur for several reasons. First, the remaining parent leaving the home causes the children in second-parent migrant households to lose the last of the family's parental care. This loss may be expected to have larger impacts on the child's life than does the first parent leaving the home (Zhang et al., 2014; Zhou et al., 2014). After the migration of the final parent, there may be no one available in the home to help the child review his or her schoolwork, and the child's domestic responsibilities may increase, decreasing his or her studying time (Chang et al., 2011; de Brauw & Mu, 2011).

Second, for first-parent migrant households, migration may lead to higher incomes, and rising incomes may be able to prove better nutrition and improved access to educational supplies (Bai et al., 2018). It may be because of the positive impact of this income that first-parent migration does not have a significant negative effect on school performance. For second-parent migration, the additional remittance income may have a smaller marginal impact on education achievement than the remittance income from first-parent migration (Du et al., 2005; Edwards & Ureta, 2003; Taubman, 1989). Combined with the potentially more negative effect of decreased parental care for second-parent migration, a smaller positive income effect may change the balance between the parental care and income effects for second-parent migration, making the net effect on academic performance more negative than for first-parent migration.

So what evidence is there that this is what is happening? First, we have shown in both Shaanxi and Qinghai (see Supplementary Materials) that second-parent migration has a more negative effect than first-parent migration. Insofar as the net effects are the sum of the income and parental effects, a more negative effect must mean a different weighing of the income and parental effects. Second, the heterogeneous effects are consistent with the reasoning in the previous paragraphs. In Shaanxi, we find that the negative impact of the departure of the second parent on academic performance was significantly larger for oldest children than for non-oldest children. As we hypothesised, when the final parent leaves, the oldest child not only loses parental care, but also may have to take over many of the parent's household responsibilities.

In addition to the evidence presented above, other sources also demonstrate that the impact of second-parent migration on grades is more negative than that of first-parent migration. While they only use the DD results as a preliminary analysis and do not focus on second-parent migration, Zhang et al. (2014)'s DD results show that second-parent migration has a more negative impact on student grades than first-parent migration in both Maths and Chinese. These negative impacts are consistent with all of our previous results and support our findings.

Our finding that the trade-off between the income and parental effects is weighted differently for first-parent and second-parent migration draws into question the results of previously published studies. While Bai et al. (2018) rejected 'the hypothesis that migration negatively affects school performance', we show that we cannot reject this hypothesis for second-parent migration. Further, Zhao et al. (2014) and other studies that use cross-sectional data to study how having a migrant parent affects educational performance cannot differentiate between first-parent and second-parent migration, a distinction that we have shown matters. At best, these studies can only provide an average of the impacts of first-parent and second-parent migration, and so their results might differ solely because the proportion of first-parent migrants to second-parent migrants differed in their samples. In general, previous studies have applied their results too widely, claiming that their results held for all types of parental migration without specifically considering the effects of second-parent migration.

5. Conclusion

In this paper, we have tried to understand how the out-migration of the second parent affects the academic performance of LBCs, and how this impact differs from that of the out-migration of the first parent. For first-parent migration, we don't find a significant negative effect on student academic performance, which may be due to a positive income effect. When the first parent migrates, rising incomes may be able to provide students with better nutrition and educational inputs that help them avoid negative effects on academic performance.

However, by comparing the change in standardised maths scores before and after second-parent migration between children with no parents left at home and those with one parent left at home, we found a significant negative impact of second-parent migration on LBCs. This more negative effect of the second parent migrating may be due to the greater negative effect of decreased parental care and the smaller positive marginal income effect of second-parent migration.

Through heterogeneous analysis, we also find that second-parent migration has a more negative effect on grades of non-boarding students and oldest children. For non-boarding students, who live at home without parental supervision, the negative effect of the decrease in parental care predominates. For oldest children, when the final parent leaves, they are more likely to do household chores and take care of younger children, decreasing their studying time.

In light of our findings, we believe policy makers should take action to help improve the situation of LBCs. One possibility is implementing an informational campaign in conjunction with a conditional cash transfer (CCT) programme. The information campaign would suggest that the final parent should stay at home to take care of the children and the CCT would provide a monetary incentive for the second parent to do so. However, it may be hard to implement this solution, not only because it's expensive, but also because it's hard to observe whether or not the final parent stays at home. Ultimately, reform of *hukou* policy could alleviate the negative effects of parental migration on the academic outcomes of LBCs. For migrant children who are unable to obtain urban *hukou*, attending urban public schools remains to be very difficult (Lai et al., 2014). If the *hukou* registration system were reformed, migrant children could live with their parents in urban areas, benefitting from the income effect without any negative parental care effects.

Although we used the placebo test to verify that our DD satisfies the assumptions for causal inference, our results could still be biased. Specifically, although we control for many observed and time-invariant unobserved factors, our results may still be subject to reverse causality and selection bias issues for which we are unable to account. For example, if a parent at home decided not to migrate because he or she worried that migrating would negatively affect his or her child's academic performance, then our results would be subject to selection bias. However, if parents did indeed decide not to migrate because they believed the grades of their children would suffer, we believe this would be an attenuation bias. Thus, we believe that we have correctly captured the direction of the true effect. While we are unable to control for time-varying endogeneity in this paper, we hope that future researchers will investigate instrumental variables approaches suited for second-parent migration and will further examine the impact of second-parent migration on the lives of LBCs. In addition, we acknowledge that our results should be interpreted in the context of developing provinces like Shaanxi and Qinghai, two relatively poor provinces that are not nationally representative.

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