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Effect of Parental Migration on the Academic Performance of Left Behind Children in North Western China

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ABSTRACT *China's rapid urbanisation has induced large numbers of rural residents to migrate from their homes in the countryside to urban areas in search of higher wages. As a consequence, it is estimated that more than 60 million children in rural China are left behind and live with relatives, typically their paternal grandparents. These children are called Left Behind Children (LBCs). There are concerns about the potential negative effects of parental migration on the academic performance of the LBCs that could be due to the absence of parental care. However, it might also be that when a child's parents work away from home, their remittances can increase the household's income and provide more resources and that this can lead to better academic performance. Hence, the net impact of out-migration on the academic performance of LBCs is unclear. This paper examines changes in academic performance before and after the parents of students out-migrate. We draw on a panel dataset collected by the authors of more than 13,000 students at 130 rural primary schools in ethnic minority areas of rural China. Using difference-in-differences and propensity score matching approaches, our results indicate that parental migration has significant, positive impacts on the academic performance of LBCs (which we measure using standardised English test scores). Heterogeneous analysis using our data demonstrates that the positive impact on LBCs is greater for poorer performing students.*

1. Introduction

China's rapid development and urbanisation has induced large numbers of rural residents to migrate from their homes in the countryside to urban areas (Hu, Cook, & Salazar, 2008; Ministry of Human Resources and Social Security [MHRSS], 2013; Wen & Lin, 2012). In the course of migration, it is common for migrants to leave their children behind in their home communities with a surrogate caregiver (Ye, Wang, Zhang, & Lu, 2006). As a consequence, in the past decade a new population has emerged in China known as Left Behind Children, henceforth LBCs (Duan & Zhou, 2005). Statistics from the Sixth Population Census show that there were more than 61 million LBCs, or children aged 0–17 with at least one migrant parent in China (All-China Women's Federation [ACWF], 2013).

The education of LBCs has drawn attention from researchers, though the literature is mixed concerning the direction of the effect of parental migration on the academic performance of LBCs (Antman, 2012; Chang,

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Dong, & MacPhail, 2011; Chen, Huang, Rozelle, Shi, & Zhang, 2009; Giannelli & Mangiavacchi, 2010; Lahaie, Hayes, Piper, & Heymann, 2009; Lu, 2012; Roy, Singh, & Roy, 2015; Wang, 2014; Xu & Xie, 2015; Yang, 2008). In some cases, researchers have found a positive relationship between parental migration and academic performance of LBCs (Chen et al., 2009; Roy et al., 2015; Yang, 2008). Research finds that this may occur through mechanisms such as relaxing household liquidity constraints (Du, Park, & Wang, 2005) and encouraging higher investments in LBCs (Ambler, Aycinena, & Yang, 2014; Antman, 2012; Edwards & Ureta, 2003; Lu & Treiman, 2011; Malik, 2015; Yang, 2008). However, some researchers have identified negative effects of parental migration (Meyerhoefer & Chen, 2011; Zhang, Behrman, Fan, Wei, & Zhang, 2014; Zhao, Yu, Wang, & Glauben, 2014; Zhou, Murphy, & Tao, 2014), finding that the negative effects are mainly due to the absence of parental care (Lahaie et al., 2009; Ye & Lu, 2011) or to the increased time LBCs spend doing on-farm or in-home work (Chang et al., 2011; McKenzie & Rapoport, 2011). Other studies have found that there is no relationship between parental migration and LBC academic performance (C. Zhou et al., 2015).

While many studies have examined the effect of being an LBC on learning outcomes, there are a number of weaknesses in the literature that may account for the mixed impacts. Some of the studies do not have valid comparison groups (Meyerhoefer & Chen, 2011). Many previous studies are based on small samples (Lu, 2012; Ye & Lu, 2011; M. Zhou et al., 2014). Other studies do not use careful/objective measures of academic performance (Chen et al., 2009).

Most studies also only examine the overall effect of being an LBC on educational outcomes and do not consider the fact that there may be important heterogeneous effects which may account for the differences in findings among the studies. For example, only a limited number of previous studies distinguish between the effects of the paternal and maternal migrant status (Antman, 2013; Chen et al., 2009; Wang, 2014; M. Zhou et al., 2014). Also, there are not many studies that show that the effect of parental migration on academic performance varies by gender (Wang, 2014; M. Zhou et al., 2014) or the mother's level of education (Sawyer, 2014).

The overall goal of this study is to examine the effects of parental migration on the academic performance of LBCs. To meet this goal, we first compare the distribution of children's scores across different types of households. Second, we use difference-in-difference and matching approaches to examine whether parental migration affects the academic performance of LBCs. Third, we examine the heterogeneous impacts of parental migration by student gender, his/her starting academic performance and his/her household social economic status.

2. Data

In order to achieve our objectives, we conducted two rounds of surveys: a baseline survey and an endline survey. A total of 13,055 students in 130 elementary schools participated in our study. We describe the study's sampling protocol and data collection approach in Supplementary Materials 3.

2.1. Parental migration

In order to measure the key independent variable, parental migration status, we collected detailed information on the migration histories of each student's parents. The information came from the survey questionnaire that was filled by students under the supervision of enumerators. In the questionnaire, we included a section that asked for the migration status of each parent during the past several months. Specifically, the questions asked (separately for each parent) whether each parent had been away from home for two months or more during the semester. 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. Field observations and interviews with key informants suggest that for most rural labourers in the study area, if they are working and living away from home for at least two months of a semester, it is almost certain that they were actually away from home for the entire year (with the possible exception of being home during holidays).[1] As a way of cross checking, we asked the homeroom teacher to verify the information on the parental migration status of each student. Based on the information of parental migration, there are two main types of households of interest in this study: migrant households (in which at least one parent out-migrated between our baseline and endline surveys) and non-migrant households (in which neither parent out-migrated between our baseline and endline surveys).

Recognising that the effect of parental migration on student performance may be affected by which family member out-migrates, we further subdivided the migrant households into six types of households: *Any Parent Migrated* households (father, mother or both parents out-migrated), *Father Migrated Only* households, *Father Migrated* households (unconditional on mother's migration status), *Mother Migrated Only* households, *Mother Migrated* (unconditional on father's migration status), and *Both Parents Migrated* households. It should be noted that the six types of households are not mutually exclusive. For brevity, when we talk about all of these households as a group, we call them *New Migrant* households to distinguish them from households that were already in the migrant labour force by the time of the baseline survey. In addition, we define *Never Migrant* households as those in which both parents stayed at home in both 2013 and 2014. Supplementary Materials Table 1 contains a list of the key independent variable names and definitions.

We use these types of parental migration variables to evaluate the effects of parental migration on the academic performance of LBCs. We make use of the variation in household migration status during the period of time between the baseline and endline surveys to evaluate the effect of migration status on school outcomes. In doing so, conceptually, our sample students are being divided into a treatment group (*New Migrant* households) and a comparison group (*Never Migrant* households). Sub-treatments in this framework are carried out using the six different types of migrant households.

It should be noted that although the two rounds of the survey that we collected enable us to identify the changes of scores of students before and after the migration of their parents, the two rounds of the survey were conducted less than one year apart. In at least one previous study, the authors showed that the duration of the absence of parents (due to migration) was an important determinant of the impact of parental migration on the educational performance of their children (for example, Jampaklay, 2006; M. Zhou et al., 2014). Estimating the impact of parental absence on educational performance of children over a longer period of time would be an interesting topic for future research. In addition, our data do not allow us to distinguish the migrated parents and newly migrated parents since those two kinds of migrant parents may have overall spent similar durations of time away from their children. Estimating the impact of migration histories on left behind children could be a direction for future research.

3. Parental migration and academic performance

Similar to the state of migration in many other rural areas in China (Rozelle, Guo, Shen, Hughart, & Giles, 1999), many households were already in the migrant labour force in 2013 when we conducted the baseline survey. Of the 12,207 households in our sample, there were 5483 (44.9%) households in which at least one parent out-migrated (Table 1, column 1). Within our sample of migrant households, we found differences in prevalence among types of migration. Of the 5483 households with out-migrants, only the father out-migrated in 2730 households, this accounts for 22.4 per cent of the total number of households or 49.8 per cent of the migrant households (column 1). In contrast, only the mother out-migrated in 560 households, which accounts for 4.6 per cent of the total households or 10.2 per cent of migrant households. According to our data, both parents out-migrated in 2193 households, which is 18.0 per cent of the total number of households or 40.0 per cent of migrant households.

We also find that the number of new migrant households rose rapidly during the study period. Among the 6724 households that did not have any migrating parents in 2013 (column 1, row 4), at least one of the parents in 2205 (32.8%) of these households entered the migrant labour force between the September 2013 baseline survey and the June 2014 endline survey. After accounting for the 1663 households that out-migrated at baseline and returned to the village at endline (column 8, rows 1–3), the total number of migrant households rose to 6025 households (49.4% of the total sample) by June

Table 1. Patterns of migration in sample households in 2013 and 2014, Qinghai Province, China

	Migration status in 2013	Migration status in 2014						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Number of households in 2013	Any Parent Migrated in 2014	Father Migrated Only in 2014	Father Migrated in 2014	Mother Migrated Only in 2014	Mother Migrated in 2014	Both Parents Migrated in 2014	Neither parent migrated in 2014
[1] Father migrated only	2730	1779	1358	1728	51	421	370	951
[2] Mother migrated only	560	353	63	221	132	290	158	207
[3] Both parents migrated	2193	1688	305	1579	109	1383	1274	505
[4] Neither parent migrated	6724	2205	1264	2028	177	941	764	4519
[5] Total number of households	12207	6025	2990	5556	469	3035	2566	6182

Notes: 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 (or those households in which households had a migrant in 2013 and in 2014 had returned home). These households are dropped from the multivariate analysis. The households in row 1, columns 2–7; row 2, columns 2–7; and row 3, columns 2–7 are always migrant households. These households are dropped from the multivariate analysis. Total new migrants (or those households in which the parents did not migrate in 2013 and migrated in 2014) are found in column 2, row 4. Never migrants are found in column 7, row 4.

2014 (column 2, row 5). This rise represents a 4.5 percentage point increase from the baseline migration level.

Our sample also included a subset of households that did not send out any migrant during the study period. Specifically, 4519 households (37.0% of the total sample) did not migrate in either period (column 8, row 4). This group of households provides the comparison group against which we can measure the impact of parental migration.

3.1. Correlation between migration and academic performance

Our descriptive results suggest that an analysis of the *change* in English test scores in relation to a valid comparison group (that is, the *Never Migrant* group) is necessary to evaluate the effect of parental migration on the academic achievement of LBCs. For example, Figure 1 shows that although students from *Both Parents Migrated, Mother Migrated Only, and Mother Migrated* households scored lower than those from the *Never Migrated* households in the endline survey, the scores of the students were already lower before their parents migrated.[2] An analysis that does not take into consideration the performance of students over two periods may misattribute a student's initial performance as a product of parental migration.

When we compare the change in standardised English test score from the baseline to the endline survey between students of *New Migrant* households and those of *Never Migrant* households, the average standardised English test score of students increased, ranging from 0.02–0.12 SD (Figure 2). This suggests that, taking into consideration the baseline test scores of students, parental migration actually may have had a positive effect on test scores.

The increases in English test scores of children from *New Migrant* households, however, may not be solely explained by parental migration. Further analysis of our data reveals that school performance

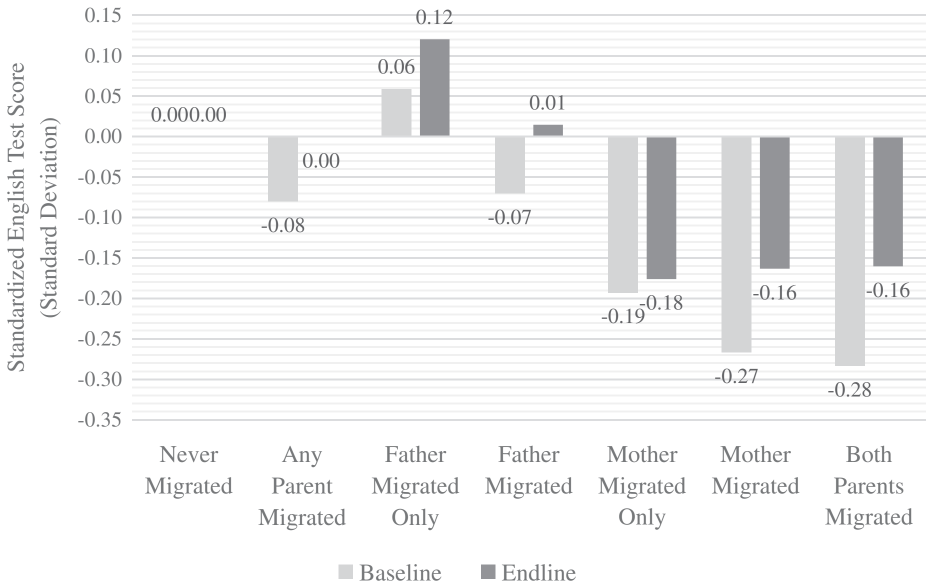

Figure 1. The standardised English test score of baseline and endline survey in different migrant households.

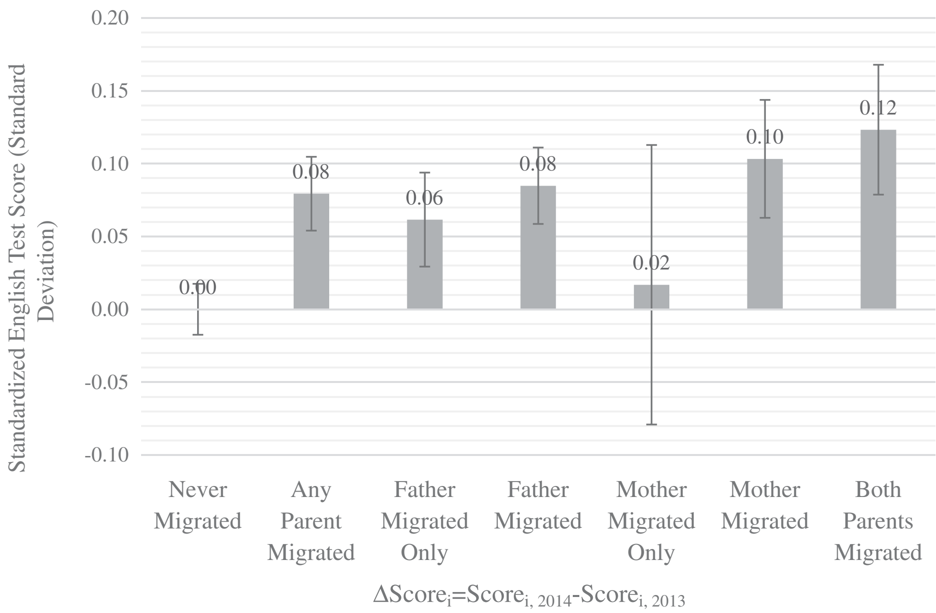

Figure 2. Change in standardised English test score before and after the parents of students out-migrate with 95 per cent Confidence Interval (*CI*) in different migrant households.

may be explained by many factors other than migration activities that change over time and differ between migrant and non-migrant households. For example, higher income could have a positive effect on the grades of children from migrant households over time that might offset any other adverse effects. Therefore, multivariate analysis is needed to explore the impact of parental migration on academic performance while holding other factors constant.

4. Methodology

In this section we use difference-in-differences and propensity score matching approaches to examine whether parental migration affects the academic performance of their LBCs. We employ difference-in-differences and matching approaches to examine if the results are robust to our choice of estimating approaches. Finally, we extend the cross-sectional matching estimator to a longitudinal setting and implement a difference-in-differences matching estimation approach in attempt to control for an additional part of unobservable factors.

4.1. Difference-in-differences approach

We employ a Difference-in-differences (DID) approach to compare the outcomes (that is, academic performance) of students in the treatment group before and after the parent(s) out-migrated to students in the comparison group. This comparison produces what we call standard DID estimator. The model we estimated is restricted and unadjusted model:

$$\Delta Score_{is} = \alpha + \beta \cdot MIG_{is} + \lambda \cdot C_c + \varepsilon_{is} \tag{1}$$

where i denotes student in school s, $\Delta Score_{is}$ is the change in standardised English test score of student i in school s between baseline survey and endline survey (that is the standardised endline English test score [standard deviation] minus the standardised baseline English test score of the same student i in school s). MIG_{is} is the treatment variable which makes β the parameter of interest. In our analysis, we have six different treatments, as discussed above, namely: *Any Parent Migrated* households; *Father Migrated Only* households; *Father Migrated* (Unconditional) households; *Mother Migrated Only* households; *Mother Migrated* (*Unconditional*) households; *Both Parents Migrated* households. The county effect is captured by λ.

In addition to the standard DID estimator (Smith & Todd, 2005), we implemented three other DID estimators: an 'unrestricted' version that includes baseline outcomes as a right hand variable, an 'adjusted' version that includes other covariates in addition to the treatment variable, and an unrestricted/adjusted model that combines the features of both the 'unrestricted' and 'adjusted' model. The unrestricted and adjusted DID estimators relax the implicit restrictions in the standard DID estimator that the coefficient associated with baseline outcomes and covariates gathered from baseline survey equals one. The combination of unrestricted and adjusted DID estimators relaxes both of these assumptions.

In summary, the models to be estimated are:

The unrestricted and unadjusted model is:

$$\Delta Score_{is} = \alpha + \beta \cdot MIG_{is} + \delta \cdot Score_{is,baseline} + \lambda \cdot C_c + \varepsilon_{is} \tag{2}$$

The restricted and adjusted model is:

$$\Delta Score_{is} = \alpha + \beta \cdot MIG_{is} + \gamma \cdot X_{is} + \lambda \cdot C_c + \varepsilon_{is} \tag{3}$$

And, the unrestricted and adjusted model is:

$$\Delta Score_{is} = \alpha + \beta \cdot MIG_{is} + \delta \cdot Score_{is,baseline} + \gamma \cdot X_{is} + \lambda \cdot C_c + \varepsilon_{is} \tag{4}$$

where the term X_{is} is a vector of covariates that are included to capture the characteristics of students, their parents and households, such as *gender, age, ethnicity, grade*, and *number of siblings*. The data that were used to create all of the covariates were collected at the baseline survey (or before parental migration). $Score_{is,baseline}$ represents the standardised baseline English test score of student i in school s.

We also use a version of Equation (4) to test for the heterogeneous effects of parental migration on the academic performance of LBCs. We do this by including an interaction term between the treatment dummy variables and the potential variables that may affect the outcome through the treatment heterogeneously. In our analysis, we include several different variables in the heterogeneous analysis, including *standardised English test score in the baseline, female, ethnic minority, only child, assets, father has junior high school or higher degrees, mother has junior school or higher degrees*.

In the analysis 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).

4.2. Propensity score matching approach

In addition to the set of DID estimators, we also used a matching approach to check and see whether our results are robust to our choice of estimators. Rosenbaum and Rubin (1983) proposed Propensity Score Matching (PSM) as a way to reduce the bias in the estimation of treatment effects with observational data sets. PSM allows the analyst to match a student in the treatment group with a similar student from the comparison group and interpret the difference in their academic performance as the effect of the parental migration activities when observable characteristics of *Never Migrant* and *New Migrant* households are continuous, or when the set of explanatory factors that determine parental migration contains multiple variables (Rosenbaum & Rubin, 1985). With the right data, it is possible to estimate the propensity scores of all households and compare the outcomes of *Never Migrant* and *New Migrant* households that have similar propensity scores.

In order to implement the matching estimator successfully, we follow a series of well-established steps (Caliendo & Kopeinig, 2008). First, since matching is only justified over the common support region, we check whether there is a large overlap in the support of the covariates between the *New Migrant* and *Never Migrant* households. Intuitively, wide common support means that there is a fairly large overlap in the propensity scores. In our study, the common support is fairly wide in our sample (Supplementary Materials Figure 1). This means that we can estimate the average treatment effect for the treated of a large portion of the sample.

In the second step, we choose the method of matching. In this study, we use the nearest neighbour matching method with replacement. The standard errors are bootstrapped using 1000 replications. The last step is to assess the matching quality. Since we do not condition on all covariates but on the propensity score alone in PSM, it has to be checked whether the matching procedure is able to balance the distribution of the relevant covariates in both the comparison and treatment group. To do so, we use balance tests described in Dehejia and Wahba (1999, 2002). The balancing tests were satisfied for all covariates.

In order to guard against the potential source of bias (shown by Abadie & Imbens, 2002), we also implemented the Bias-Corrected Matching (BCM) estimator developed by Abadie and Imbens (2006). To minimise geographic mismatch, we enforce exact matching by county. Each treatment observation is matched to three control observations with replacement, which is few enough to enable exact matching by county for nearly all observations but enough to reduce the asymptotic efficiency loss significantly (Abadie & Imbens, 2006). Matching is based on a set of nine covariates, including *female, age, ethnic minority, 5th grade, boarding student, assets, father has junior high school or higher degrees, mother has junior or higher degrees, and number of siblings*, which are time-invariant or were measured in the baseline survey (see Table 2). The weighting matrix uses the Mahalanobis metric, which is the inverse of the sample covariance matrix of the matching variables.

Finally, since all matching methods only match observations based upon observable covariates, they do not account for all unobservable covariates. To control for part of the unobservable factors, in particular those factors that are time-invariant, we extended the cross-sectional matching estimator to a longitudinal setting and implemented a difference-in-differences matching estimator (DDM). When implementing DDM, we use both PSM and BCM methods.

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

Control variables	Total	Never migrant	Any Parent migrated		Father migrated only		Father migrated		Mother migrated only		Mother migrated		Both parents migrated	
	mean (s.e.)	mean (s.e.)	mean (s.e.)	H0: (2) = (3) Difference	mean (s.e.)	H0: (2) = (5) Difference	mean (s.e.)	H0: (2) = (7) Difference	mean (s.e.)	H0: (2) = (9) Difference	mean (s.e.)	H0: (2) = (11) Difference	mean (s.e.)	H0: (2) = (13) Difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Characteristics of the students														
[1] Female (1 = female; 0 = male)	0.49	0.49	0.48	−0.01	0.49	0.00	0.48	−0.01	0.45	−0.04	0.45	−0.03*	0.46	−0.03
	(0.50	(0.50)	(0.50)	(0.01)	(0.50)	(0.02)	(0.50)	(0.01)	(0.50)	(0.04)	(0.50)	(0.02)	(0.50)	(0.02)
[2] Age (years)	10.83	10.77	10.97	0.20***	10.92	0.18***	10.97	0.20***	10.95	0.15*	11.03	0.21***	11.05	0.23***
	(1.11)	(1.10)	(1.13)	(0.04)	(1.12)	(0.04)	(1.13)	(0.04)	(1.09)	(0.08)	(1.13)	(0.06)	(1.14)	(0.06)
[3] Ethnic minority (1 = yes; 0 = no)	0.51	0.50	0.54	0.04*	0.49	0.03*	0.54	0.04*	0.54	0.02	0.61	0.04	0.62	0.05
	(0.50)	(0.50)	(0.50)	(0.02)	(0.50)	(0.02)	(0.50)	(0.02)	(0.50)	(0.04)	(0.49)	(0.03)	(0.48)	(0.03)
[3a] Hui Minority (1 = yes; 0 = no)	0.30	0.32	0.26	−0.05*	0.24	−0.03**	0.26	−0.05*	0.26	−0.08**	0.29	−0.07	0.30	−0.07
	(0.46)	(0.47)	(0.44)	(0.03)	(0.43)	(0.02)	(0.44)	(0.03)	(0.44)	(0.04)	(0.45)	(0.04)	(0.46)	(0.05)
[3b] Tibetan (1 = yes; 0 = no)	0.11	0.08	0.17	0.08***	0.12	0.05***	0.16	0.08***	0.20	0.11***	0.23	0.13***	0.23	0.13***
	(0.31)	(0.27)	(0.37)	(0.02)	(0.32)	(0.01)	(0.37)	(0.02)	(0.40)	(0.04)	(0.42)	(0.04)	(0.42)	(0.04)
[3c] Tu minority (1 = yes; 0 = no)	0.05	0.04	0.06	0.02**	0.08	0.03***	0.06	0.02**	0.05	0.01	0.04	0.01	0.04	0.01
	(0.21)	(0.19)	(0.24)	(0.01)	(0.27)	(0.01)	0.24	(0.01)	(0.22)	(0.02)	(0.20)	(0.01)	(0.19)	(0.01)
[4] 5th grade (1 = yes; 0 = no)	0.52	0.53	0.51	−0.02	0.52	−0.01	0.51	−0.02	0.53	0.00	0.50	−0.03	0.49	−0.04*
	(0.50)	(0.50)	(0.50)	(0.02)	(0.50)	(0.02)	(0.50)	(0.02)	(0.50)	(0.04)	(0.50)	(0.02)	(0.50)	(0.02)
[5] Boarding student (1 = yes; 0 = no)	0.15	0.12	0.22	0.10***	0.20	0.07***	0.22	0.10***	0.19	0.07**	0.24	0.13***	0.26	0.14***
	(0.36)	(0.32)	(0.41)	(0.02)	(0.40)	(0.02)	(0.41)	(0.02)	(0.39)	(0.03)	(0.43)	(0.03)	(0.44)	(0.03)
Characteristics of the parents and the households														
[6] Log (asset)	9.59	9.61	9.55	−0.06***	9.55	−0.06***	9.56	−0.05***	9.52	−0.08	9.55	−0.04	9.56	−0.04

(*continued*)

Table 2. (*Continued*)

Control variables	Total	Never migrant	Any Parent migrated		Father migrated only		Father migrated		Mother migrated only		Mother migrated		Both parents migrated	
	mean (s.e.)	mean (s.e.)	mean (s.e.)	H0: (2) = (3) Difference	mean (s.e.)	H0: (2) = (5) Difference	mean (s.e.)	H0: (2) = (7) Difference	mean (s.e.)	H0: (2) = (9) Difference	mean (s.e.)	H0: (2) = (11) Difference	mean (s.e.)	H0: (2) = (13) Difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	(0.47)	(0.39)	(0.60)	(0.02)	(0.50)	(0.02)	(0.54)	(0.02)	(1.06)	(0.08)	(0.70)	(0.03)	(0.59)	(0.02)
[7] Father has at least junior high school degree (1 = yes; 0 = no)	0.49	0.52	0.44	−0.07***	0.49	−0.05***	0.43	−0.08***	0.48	−0.02	0.37	−0.10***	0.35	−0.12***
	(0.50)	(0.50)	(0.50)	(0.01)	(0.50)	(0.02)	(0.50)	(0.02)	(0.50)	(0.04)	(0.48)	(0.02)	(0.48)	(0.02)
[8] Mother has at least junior high school degree (1 = yes; 0 = no)	0.36	0.39	0.30	−0.08***	0.32	−0.09***	0.29	−0.09***	0.36	−0.00	0.26	−0.08***	0.24	−0.10***
	(0.48)	(0.49)	(0.46)	(0.01)	(0.47)	(0.02)	(0.45)	(0.02)	(0.48)	(0.03)	(0.44)	(0.02)	(0.43)	(0.02)
[9] Number of siblings	1.57	1.54	1.65	0.10**	1.53	0.07	1.64	0.10**	1.67	0.07	1.81	0.13*	1.84	0.14*
	(1.51)	(1.45)	(1.61)	(0.05)	(1.41)	(0.05)	(1.61)	(0.05)	(1.67)	(0.11)	(1.84)	(0.07)	(1.87)	(0.08)
[10] Number of Observations	6724	4519	2205	6724	1264	5783	2028	6547	177	4696	941	5460	764	5283

Notes: * significant at 10 per cent; ** significant at 5 per cent; *** significant at 1 per cent. Mean values are reported in the table with robust standard errors in parentheses clustered at school level. County dummies are controlled. The within-school difference between column (2) and column (3) is calculated by regressions of each of row variables on the dummy variable that represent *Any Parent Migrated* households. Similar for the rest.

5. Results of multivariate analysis

The results from the DID analysis using Equations (1)–(4) for the version of model that uses the *Any Parent Migrated* household variable as the treatment demonstrate that the models perform fairly well and are consistent with our intuition. The coefficients on some of the control variables are also in accordance with our intuition (Table 3). For example, when we use the unrestricted and adjusted specification of the empirical model, the scores of older students drop relatively more than those of younger students. This finding might be considered reasonable since, ceteris paribus, students that enter elementary school at an older age may have an initial advantage (because they are relatively more mature) that gradually disappears as younger children catch up over the course of primary school (Fredriksson & Öckert, 2005). Additionally, when a student is from a household that is part of a non-Han ethnic minority group, the student's score drops relatively more than Han students. There are many studies that show the academic performance of ethnic minority students in China lags behind those of Han students (Gustafsson & Sai, 2014; Yang et al., 2015). In the rest of the paper we focus

Table 3. Difference-in-differences regression results analysing the effects of migration activities of parents on school performance of students, Qinghai Province, China

Dependent variable: $\Delta Score_i = Score_{i,2014} - Score_{i,2013}$	Restricted & Unadjusted	Unrestricted & Unadjusted	Restricted & Adjusted	Unrestricted & Adjusted
VARIABLES	(1)	(2)	(3)	(4)
Treatment variable (MIG_i)				
[1] Any Parent Migrated (1 = yes; 0 = no)	0.08***	0.04**	0.06***	0.04**
	(0.02)	(0.02)	(0.02)	(0.02)
Characteristics of the students				
[2] Female (1 = female; 0 = male)			0.07***	0.15***
			(0.02)	(0.02)
[3] Age (years)			−0.01	−0.05***
			(0.01)	(0.01)
[4] Ethnic minority (1 = yes; 0 = no)			−0.00	−0.05*
			(0.03)	(0.02)
[5] 5th grade (1 = yes; 0 = no)			0.04	0.07**
			(0.04)	(0.03)
[6] Boarding student (1 = yes; 0 = no)			0.17***	0.08**
			(0.04)	(0.04)
Characteristics of the parents and the households				
[7] Log (asset)			−0.01	−0.00
			(0.02)	(0.01)
[8] Father has at least junior high school degree (1 = yes; 0 = no)			−0.02	0.03**
			(0.02)	(0.01)
[9] Mother has at least junior high school degree (1 = yes; 0 = no)			−0.07***	−0.03
			(0.02)	(0.02)
[10] Number of siblings			0.00	−0.01
			(0.01)	(0.01)
[11] Standardised pre English test score		−0.35***		0.29*
(standard deviation)		(0.03)		(0.16)
[12] County dummy	YES	YES	YES	YES
[13] Constant	0.02	−0.19***	0.24	6,724
	(0.03)	(0.04)	(0.18)	0.20
[13] Number of observations	6,724	6,724	6,724	6,724
[14] R-squared	0.01	0.17	0.03	0.20

Notes: * significant at 10 per cent; ** significant at 5 per cent; *** significant at 1 per cent. Robust standard errors in parentheses clustered at school level.

mainly on the results from the unrestricted and adjusted model. We do so because this regression has a higher goodness of fit statistic.

One of the most important findings in Table 3 is that we reject the hypothesis that parental migration negatively affects the academic performance of children. In all four models, the coefficient of the *Any Parent Migrated* household dummy variable is not negative. In fact, the coefficients are all positive and significantly different from zero. The magnitudes of the coefficients range from 0.04 to 0.08 SD. This means that, everything else held constant, after any parent in a household out-migrated between baseline and endline surveys, their child's standardised English test scores actually rose relative to the children of *Never Migrant* households. In other words, unlike claims made by some researchers (Meyerhoefer & Chen, 2011; Zhang et al., 2014; Zhao et al., 2014; M. Zhou et al., 2014), according to the results of the analysis in Table 3, parental migration did not hurt the academic performance of LBCs. At least in our migrant households, migration improved school performance.

The results hold when we examine other types of migrant households: we do not find any negative effects of parental migration on student academic performance (Table 4). For each of the four specifications, we look at the effect of parental migration on academic performance in all six types of migrant households. In 22 out of the 24 cases the coefficient is positive. The coefficients are only negative for *Mother Migrated Only* households (column 2, row 4). In each of these two cases,

Table 4. Difference-in-differences regression results analysing the effects of migration activities of parents on school performance of students in all six types of migrant households, Qinghai Province, China

Dependent variable: $\Delta Score_i = Score_{i,\ 2014}\text{-}Score_{i,\ 2013}$

	Restricted & Unadjusted	Unrestricted & Unadjusted	Restricted & Adjusted	Unrestricted & Adjusted
Treatment variables	(1)	(2)	(3)	(4)
[1] Any Parent Migrated	0.08***	0.04**	0.06***	0.04**
	(0.02)	(0.02)	(0.02)	(0.02)
No. of observations	6,724	6,724	6,724	6,724
R^2	0.01	0.17	0.03	0.20
[2] Father Migrated Only	0.06***	0.03	0.04**	0.03
	(0.02)	(0.02)	(0.02)	(0.02)
No. of observations	5,783	5,783	5,783	5,783
R^2	0.01	0.16	0.02	0.19
[3] Father Migrated (unconditional)	0.08***	0.04**	0.06***	0.04**
	(0.02)	(0.02)	(0.02)	(0.02)
No. of observations	6,547	6,547	6,547	6,547
R^2	0.01	0.17	0.03	0.20
[4] Mother Migrated Only	0.01	−0.04	0.00	−0.04
	(0.05)	(0.04)	(0.04)	(0.04)
No. of observations	4,696	4,696	4,696	4,696
R^2	0.00	0.17	0.03	0.20
[5] Mother Migrated (unconditional)	0.10***	0.04*	0.07***	0.04*
	(0.02)	(0.02)	(0.02)	(0.02)
No. of observations	5,460	5,460	5,460	5,460
R^2	0.01	0.18	0.03	0.21
[6] Both Parents Migrated	0.12***	0.06**	0.09***	0.07***
	(0.03)	(0.03)	(0.02)	(0.02)
No. of observations	5,283	5,283	5,283	5,283
R^2	0.01	0.18	0.03	0.21

Notes: * significant at 10 per cent; ** significant at 5 per cent; *** significant at 1 per cent. Robust standard errors in parentheses clustered at school level. County dummies are controlled. The full version of the regressions from Equations (1)–(4) is not reported for brevity purpose but is available from the authors upon request.

however, there is no statistically significant effect. Interestingly, when the father out migrated (column 4, row 3) or mother out migrated (unconditional) (column 4, row 5) or both parents out migrated (column 4, row 6), the standardised English test scores of LBCs improved significantly.

So why is it that parental migration does not appear to have a negative effect on the academic performance of LBCs and in some cases even appears to have a positive effect? Although we cannot answer this question from our analysis, one possible reason is that the income effect of remittances is relatively large compared to the adverse effect of lower parental care. If parental migration leads to higher income (Du et al., 2005), the migrant households that experience rising incomes may be able to provide LBCs with better nutrition (Cueto & Chinen, 2008; Hoyland, Dye, & Lawton, 2009; Shemilt et al., 2004), improve their access to higher quality, better educational supplies and/or burden their children with less housework (Lu & Treiman, 2011). With the addition of these household resources and the lessening of burdens, parental migration may have a positive effect on academic performance. The positive income effect is probably behind our finding that the largest positive effects are found in the *Both Parents Migrated* households (Table 4, row 6). This result may arise since the family income would improve more when both parents out-migrated compared to the case of the other types of *New Migrant* households. This income effect also appears to be large enough to offset any negative effects of parental absence – such as the decline in parental care. Thus, on the whole, our results demonstrate that parental migration has a net positive effect on LBC academic performance when both parents out-migrate.

Unlike some previous studies that were based on surveys conducted in localities in Central China's major labour exporting provinces (for example, Zhang et al., 2014; M. Zhou et al., 2014), this study is based on a dataset gathered from Qinghai province. Considering the fact that Qinghai is one of the poorest provinces in China in terms of per capita disposable income of rural residents (National Bureau of Statistics of China [NBSC], 2014a), if there are diminishing returns to expenditures from income as income rises, it could be that remittance transfers play a more important role (or has a higher positive effect on the welfare of those in the family) in poor locations (such as in rural Qinghai). In addition, according to statistical yearbooks and official reports from the National Bureau of Statistics of China, it is clear that nearly 80 per cent of the migrants in Qinghai are intra-provincial in 2013 (NBSC, 2014b). Given that intra-provincial migration may produce less stress on a family (and the children's home environment) due to the fact that parents are more closely in contact with the family and can more easily come home when there are family issues to deal with, it could be that this might help account for the positive impact of parental migration on LBC learning in this study. In other words, it could be that there is a positive income effect but that (if present) the decline in care effect is less strong. Therefore, if one were to replicate the study in a relatively richer area (say in a location in Central China), the positive effects of parental migration on educational performance might be lower.

6. Results from matching

The results of the cross-sectional matching analysis, regardless of the method of matching, also demonstrates that parental migration has no significant negative effect on LBC academic performance. When propensity score matching is used to examine the effect of parental migration for all six types of *New Migrant* households, there are no cases in which the coefficient on the treatment variable is negative and statistically significant (Table 5, column 1, rows 1a–6a). The same is true when Bias-Corrected Matching is used (column 1, rows 1b–6b).

In fact, results from matching are quite similar to those from the DID analyses. When we use Bias-Corrected Matching, we find that the coefficients on the treatment variables in the *Any Parent Migrated* household, the *Father Migrated* (unconditional) household, the *Mother Migrated* household and the *Both Parents Migrated* household are positive and statistically significant. The magnitudes of the coefficients also are similar.

In addition, the findings remain largely the same when the DDM estimator is used (Table 5, column 2). Regardless of whether we use PSM or BCM, none of the coefficients of any of the treatment variables are significantly negative. In fact, most of them are positive and significant. Hence, whether using DID, PSM or DDM, we find no significant negative effects of parental migration on LBC academic performance.

Table 5. Evaluating the effects of migration activities of parents on school performance of students in all six types of migrant households using matching and difference-in-differences matching, Qinghai Province, China

	(1)			(2)		
	Matching			Difference-in-differences matching		
Treatment variables	Average treatment effect for the treated	Std. Err.	t-stat/z-value	Average treatment effect for the treated	Std. Err.	t-stat/z-value
Any Parent Migrated						
[1a] Propensity score matching	0.11***	0.04	3.00	0.08***	0.02	3.58
[1b] Bias corrected matching	0.07***	0.02	4.37	0.07***	0.02	4.05
Father Migrated Only						
[2a] Propensity score matching	0.01	0.05	0.25	0.03	0.03	1.19
[2b] Bias corrected matching	0.06***	0.02	3.10	0.07***	0.02	3.02
Father Migrated (unconditional)						
[3a] Propensity score matching	0.09***	0.04	2.35	0.06***	0.02	2.77
[3b] Bias corrected matching	0.08***	0.02	4.51	0.08***	0.02	4.05
Mother Migrated Only						
[4a] Propensity score matching	0.01	0.11	0.11	−0.02	0.07	−0.26
[4b] Bias corrected matching	0.02	0.05	0.46	0.05	0.05	0.91
Mother Migrated (unconditional)						
[5a] Propensity score matching	0.08*	0.05	1.82	0.02	0.03	0.55
[5b] Bias corrected matching	0.09***	0.02	3.73	0.08***	0.03	3.25
Both Parents Migrated						
[6a] Propensity score matching	0.10**	0.05	2.01	0.08***	0.03	2.35
[6b] Bias corrected matching	0.10***	0.02	4.02	0.09***	0.03	3.26

Notes: Propensity scores are estimated using the same set of covariates as in Table 2.
* significant at 10 per cent; ** significant at 5 per cent; *** significant at 1 per cent. t-stats are reported for propensity score matching and z-values are reported for bias-corrected matching in parentheses. We use propensity scores as a tool to enforce a common support. We use the nearest neighbour matching with replacement. Following Smith and Todd (2005), we match students based on the log odds ratio and standard errors are bootstrapped using 1000 replications. To minimise geographic mismatch, we enforce exact matching by county. Each treatment observation is matched to three control observations with replacement. The weighting matrix uses the Mahalanobis metric, which is the inverse of the sample covariance matrix of the matching variables.

7. Conclusions

Our paper has tried to understand whether LBC academic performance suffers when the father, mother or both parents of children migrate from their home communities to the city. Despite the common perception, our results – somewhat surprisingly – show that there seem to be no significant negative effects of parental migration on the academic performance of LBCs. Comparing the change in the standardised English test scores before and after parents out-migrated between children from migrant households and those from non-migrant households, we can reject the hypothesis that parental migration negatively affects LBC academic performance. In fact, in the analysis of many types of migrant households, migration is shown to have a statistically significant and positive effect on LBC academic performance. We acknowledge that our results are interpreted in the context of Qinghai province, a relatively poor province that is not one of China's major labour exporting provinces.

In addition, we also sought to explain how the impacts of parental migration vary for different subgroups, that is, different types of migrant households, of our sample. Results from our data show that the positive impact of parental migration on LBCs is greater for poor performing students. However, the positive impact may be offset if the mother of an LBC has at least a junior high school degree. In contrast, we find no evidence of heterogeneous effects by other student demographic and family characteristics.

Based on these results, it might be tempting to conclude that policy-makers do not need to take any action (to help LBCs) since there are no measurable negative effects of migration on school performance. If there were, education officials might want to reduce class sizes or hire more qualified teachers to improve the mentoring programme in schools in which there were many LBCs. Boarding schools might offer some of the services that parents originally carried out before they entered the migrant labour force. However, in coming to this conclusion, caution needs to be taken. In fact, boarding students (as a way to replace the presence of parents) is not costless. In empirical work on rural Chinese schools it has been shown that when students live in boarding school (holding all else constant), there can be negative impacts in a number of dimensions, including on academic performance, health, nutrition and in-class behaviour (Luo et al., 2009; Mo et al., 2012; Wang, Shi, Yue, Lou, & Medina, 2016).

Ultimately, measures can be promoted to offer the children of migrants who live in China's cities better access to urban schools so parents would not have to leave their children behind. However, all of these programmes are costly. Although there might be good reason to implement such policies anyhow, according to our results, they should not be carried out on the ground of the negative effect of migration on school performance. In addition, since both groups of children (children from migrant households and non-migrant households) perform poorly on academic performance, we recommend that special programmes designed by policy-makers to improve education among left behind children be expanded to cover all children in rural China.

Although we have tried a number of alternative approaches, and although the findings are largely robust, if the assumptions underlying our methodologies were not valid, our estimates could be bias. Even though we controlled for many observed and time-invariant unobserved factors, there still may be factors that are known to the parents of migrants and potential migrants but are not observable to the econometrician. For example, it may be that all parents who were in the village with their children in the baseline survey worry about whether or not their migration decision would negatively affect the academic performance of their children. If it is the case that those parents who – though having an opportunity to migrate – believed that the grades of their children would suffer decided not to migrate, while those that believed their children's grades would not suffer decided to migrate, then our results would be subject to selection bias.

If there was such a selection bias and we did not account for it (as we were unable to – due to the absence of any effective instrumental variable), would our results be useless? We believe not. We believe even if there was a selection bias our results are showing that when rural parents out-migrate, the academic performance of their children do not suffer. It is true that part of the reason for the non-negative effect may be exactly this selection effect – parents do not go when they believe the scores of the children would suffer. But, from society's point of view, there is less cost in terms of academic performance of its children due to parental migration.

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Notes

1. In some sense, the periods of time away from home possibly are quite short. Hence, if we find that there is no result, we have to consider the possibility that the insignificant result was due to the short time period of migration and that if the period of migration was longer, there might be an effect. Future research should try to collect fuller migration histories of families. However, getting such information is more difficult and costly since children do not often know and parents (who best know the histories) are frequently not at home.
2. In fact, there might be two reasons why LBCs whose mothers out-migrated (no matter if the fathers out-migrated) are doing worse than other children at baseline. First, families in which Mother Migrated Only may have other problems beyond the mother leaving for work. Since our answers are given by students who are sitting in class, it could be that children are being told their mother had out-migrated for work when the mother had really separated for other reasons. Children may also know but be unwilling to admit to the fact that their parents had separated or divorced. If the family environment is negatively affected by the marriage problems of the parents then it is possible that this would be reflected in the poor performance in school by children of such households.

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