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Order Matters: The Effect of Second-Wave Migration on Student Academic Performance in Northwest China

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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 from the city to the countryside, it has also created a generation of left-behind children, or LBCs, who remain in the countryside when their parents migrate (Sicular et al. 2006; Luo and Ximing, 2010). This is not a trivial issue. As the number of rural-urban migrant workers has increased, reaching 168 million in 2015, the number of LBCs has also increased, exceeding 60 million in 2010 (NBSC 2014, 2015; ACWF, 2013). 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 and Hua, 2001; Sicular et al., 2006; Qian and Smyth, 2008).

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 academic performance by easing liquidity constraints and increasing investment in children and their education (McKenzie, 2005; Calero et al., 2009; Lu, 2012; Amuedo-Dorantes and Pozo, 2010). On the other hand, parental absence could harm academic performance by decreasing parental care and increasing the domestic and farming responsibilities of LBCs (McKenzie, 2005; Chang et al., 2011; deBrauw and Mu, 2011; Lu, 2012). 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 et al. (2009) and Bai et al. (2015), 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. (2015) 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 et al. (2014) and Zhou et al. (2014) found significant negative impacts of the migration of both parents on the academic performance of their children. Specifically, Zhao et al. (2014) found that parental migration can decrease a child's math score by more than 15% 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. (2014), 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 study areas consisting of a few towns or a single county (e.g., Zhang et al., 2014), thus causing their findings to lack representativeness.

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-wave* migration (migration during the first period of time in which any parent migrates) and *second-wave* migration (migration when the remaining parent leaves the home). To our knowledge, no research team has sought to empirically differentiate the impact of first-wave migration from second-wave migration.

We might expect that the relative strength of the income and parental care effects is different for first-wave migration and second-wave migration for several reasons. First, second-wave 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. We expect that losing the last of a family's parental care might be expected to have large affects on many aspects of the child's life (Zhang et al., 2014; Zhou et al., 2014). There would not be a parent around to monitor or help a child with homework, and household responsibilities might also fall to the child. Thus, we hypothesize that the negative effect of decreased parental care is greater when the final parent leaves the home than when a first-wave parent out-migrates.

Second, since the family was already receiving remittances from the first parent, we believe that additional remittance income from a second-wave migrant parent would have a smaller marginal impact on educational achievement than the original remittance income from the first-wave migrant parent (Taubman, 1989; Edwards and Ureta, 2003; Du et al., 2005). 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. If this is true, then if a household has already eased their credit constraints with the remittance income from the first migrant, then the income from the second migrant will likely not have as large of an effect on academic performance. 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. (2015) argues may improve academic performance, then the remittance income from the second migrant will likely have a smaller impact. Thus, the positive effect of extra income that the migrant parent generates might be weaker for second-wave migration than for first-wave migration.

It for this reason that we believe that the nature of migration—that is, whether it is first-wave migration or second-wave migration— has different effects on the academic performance of LBCs. If so, and one set of studies was studying (mostly) first-wave migration, while another set of studies was studying second-wave 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-wave migration has a relatively larger negative effect (or a less positive effect) on academic performance than does first-wave 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-wave and second-wave migration on academic performance. Finally, this paper seeks to understand what types of children (and children from what types of households) are most affected by second-wave 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 choose 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 randomly selected four counties was about 4,000RMB ($650) per year in 2011, far below rural China's average per capita income in 2011 of 6,977 RMB (US $1,134—NBSC, 2011).

Southern Shaanxi is also known as an area of high outmigration (Chan, 2013; Chang, 2014). Low per capita endowments of land in villages characterized by fragile soils and steep gradients give households an extra impetus to seek employment outside of the village. Almost 100 percent of the individuals in our sample are Han; there are few non-Han ethnic minority households. Because of this, there are few language (or cultural) barriers to outmigration.

After choosing the counties, in the second step of our sampling process we obtained a comprehensive list of all *wanxiao* (elementary schools with six full grades, grades one through six) in each of our sample counties. The lists came from each county's local bureau of education. Based on these lists, we randomly selected 72 schools in Ankang Prefecture that contain six full grades 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. 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 standardized examinations. Second, we excluded sixth grade students because the study started in June 2011 and because the study extended into the next academic year, the sixth grade students would have already graduated and exited our sample. Finally, we excluded fourth graders because we believed third and fifth graders 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 sample, giving a total sample size of 5,104 students.

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 et al., 2015; Mo et al., 2014). At the time of the endline survey, we were able to follow up with 5,002 students.

While our main focus in this section is on the sample from Shaanxi province, later in the paper we will look at the data set examined by Bai et al. (2015) as an additional test of how the effects of first and second-wave migration differ. The sample in Bai et al. is composed of 13,055 fourth and fifth grade students in rural Qinghai province who were given a standardized English test in September 2013 and June 2014.

2.2 Data Collection

The research team conducted both rounds of surveying in all 72 sample schools. The baseline survey was conducted with all third and fifth grade students in June 2011, at the end of the spring semester. The endline survey was conducted one year later in June 2012 when children in our sample were completing fourth and sixth grade. 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 standardized math 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 standardized test scores instead of raw test scores to make student performance comparable for different grades, classes, time periods, and cohorts. We standardized test scores for each student by subtracting the mean of the comparison group at the baseline (defined below) and dividing by the standard deviation (SD) of the comparison group. Therefore, a student with a standardized score of 0.2 scored 0.2 standard deviations above the average of the comparison group at the baseline. We standardized 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, 2014a). 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 laborers, 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-wave migrant households and second-wave migrant households. In first-wave 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 at least one parent outmigrated and was away from home during the endline survey. In second-wave 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.

We use changes in parental migration status between the baseline and endline surveys to examine and compare the effects of first-wave and second-wave migration on academic performance. To analyze first-wave 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 any parent migrated between the baseline and endline surveys (*any parent migrated households*). The comparison group is made up of households in which neither parent migrated between the baseline and endline surveys (*never migrant households*).

For second-wave 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-wave 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 (*one 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.

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*, *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*. 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. Using these additional variables as controls allows us to more efficiently measure this effect by controlling for variables that may affect school performance. Certain additional variables also allow us to explore whether migration has heterogeneous effects on academic performance across children and households.

2.3 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 describe the prevalence of different types of migrant households. We then provide a detailed description of the different waves of migration: first-wave migrant households and second-wave migrant households. Finally, we present correlations between migration status and academic performance by comparing changes in academic performance between periods with changes in migration status.

2.3.1 First- and Second-Waves of Migration

This study focuses on the effects of different waves of parental migration on student academic performance. To examine and compare the effects of first-wave and second-wave migration on academic performance, we create separate treatment and comparison groups for each wave.

For first-wave parental migration, we restrict our sample to the 2,209 households (44.2% of total sample) in which both parents stayed at home in the baseline survey (column 1, row 4). Using this sample we then define a treatment and comparison group. Specifically, the 629 households (28.5% of the first-wave sample) in which the first parent to leave the home does so between baseline and endline surveys are the treatment group (Table 1, column 2, row 4). In short, these households are those who migration status changed during the study period from having no migrating parent during the baseline to having one or more parent out-migrating during the endline (*any parent migrated households*). In contrast, the 1,580 households (71.5% of the 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 migrant households*).

As for second-wave parental migration, the 222 households in which exactly one parent migrated in 2011 but both parents migrated in 2012 (column 7, rows 1-2) are those that 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 (*one parent migrated households*).

2.3.2 Correlation between Migration and Academic Performance

For first-wave migrant households, the descriptive results suggest that scores of students in the treatment group, *any parent migrated* households, decreased more than scores of students in the control group, *never migrant* households. For the comparison group, the mean of standardized math test scores was 0 at the baseline survey and -1.26 at the endline survey (Table 2, column 1-3, row 1). Note, because we standardized 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 treatment group, the mean score at the time of the baseline survey was -0.06 SD (column 1, row 2). By the endline survey, the average scores of students in the treatment group decreased by 1.27 SD to -1.33 (column 2, row 2). This means that the scores of students in the treatment group decreased by 0.01 SD more between the baseline and endline surveys than did the scores of students in the comparison group (column 3, row 3). However, this difference is small in magnitude and not statistically significant (column 4, row 3).

For second-wave migration, *both parents migrated* households are the treatment group and *one parent migrated* households are the comparison group. As before, the mean standardized test score for the comparison group was 0 at the baseline survey, and the mean standardized test score decreased to -1.29 SD by the time of the endline survey (Table 2, column 1-3, row 4). For the treatment group, the mean score at the time of the baseline survey was -0.20 SD (Table 2, 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 comparison group (column 3, row 6). However, these results are, again, not statistically significant (column 4, row 6).

These findings, that both first- and second-wave 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-wave and second-wave parental 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 the changes in academic performance before and after student's parent(s) out-migrated to students in the comparison group. This comparison produces the standard DD estimator. In the first specification of our model, we use a *restricted and unadjusted* model:

$$\Delta Score_{is} = \alpha + \beta \cdot MIG_{is} + \lambda \cdot S_s + \varepsilon_{is} \quad (1)$$

where *i* denotes student *i* in school *s*, $\Delta Score_{is}$ is the change in standardized math 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. In our analysis of first-wave migration, our main treatment group is *any parent migrated* households. In our analysis of second-wave migration, our treatment group is *both parents migrated* households. The relevant comparison groups were described in the section above. The school effect is captured by λ. Note that we call this model restricted because this model implies a restriction that the coefficient associated with baseline grades equals one. We call the model unadjusted because it does not adjust for additional covariates.

In addition to the standard *restricted and unadjusted* DD estimator (Smith and Todd, 2005), we implement three other DD estimators: an "unrestricted" version that includes baseline grades as a right hand variable (*unrestricted and unadjusted*), an "adjusted" version of the model that includes a series of control variables from the baseline survey in addition to the treatment variable *(restricted and adjusted*), and an *unrestricted and adjusted* model that combines the features of both the "unrestricted" and "adjusted" models. The unrestricted and adjusted DD estimators relax the implicit restrictions in the standard DD estimator that the coefficient associated with baseline grades and covariates gathered from the baseline survey equals one. The combination of unrestricted and adjusted DD estimators relaxes both of these assumptions. In summary, the additional models to be estimated are as follows:

The unrestricted and unadjusted model is:

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

The restricted and adjusted model is:

$$\Delta Score_{is} = \alpha + \beta \cdot MIG_{is} + \gamma \cdot X_{is} + \lambda \cdot S_s + \varepsilon_{is} \quad (3)$$

And, the unrestricted and adjusted model is:

$$\Delta Score_{is} = \alpha + \beta \cdot MIG_{is} + \delta \cdot Score_{is,baseline} + \gamma \cdot X_{is} + \lambda \cdot S_s + \varepsilon_{is} \quad (4)$$

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, grade, boarding status, repeated a grade, oldest child, 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 assists with homework*. The data that were used to create all of the covariates were collected at the baseline survey (before the migration event). $Score_{is,\ baseline}$ represents the standardized baseline math test score of student i in school s.

We also use a version of equation (4) 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:

$$\Delta Score_{is} = \alpha + \beta_1 \cdot MIG_{is} + \beta_2 \cdot D_{is} + \beta_3 \cdot MIG_{is} \cdot D_{is} + \delta \cdot Score_{0is} + \gamma \cdot X_{is} + \lambda \cdot S_s + \varepsilon_{is} \quad (5)$$

where the coefficient on the interaction term, β_3, indicates the heterogeneous treatment effect. In our analysis, we include several variables in the DD matrix, such as *standardized baseline math score*, *female*, *age, grade, repeated a grade, boarding student, only child, oldest child*, *assets*, *father has at least a junior high school degree*, *mother has at least a junior high school degree, family member assists with homework,* and *mother migrated during second wave*.

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, this is merely an assumption. It is possible that even without the treatment, the treatment and comparison groups would have behaved differently because of something fundamentally different about the behavior 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. If the estimated results from the DD model find that the outcomes of the treatment and control groups do not change (in a statistically significant sense) during the placebo period, such findings support the validity of the parallel trend assumption.

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-wave migration sample. These treatment and comparison groups are the same second-wave 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. That is, the parents of students in the treatment group migrated between the baseline and endline surveys, after the period analyzed in the placebo test. Therefore, we hope that the treatment and comparison groups moved in parallel between the pre-baseline and baseline surveys. More specifically, we use our DD estimator models to test whether the coefficient on the parental migration treatment variable is significantly different from zero for the pre-baseline to baseline period.

4. Results of Multivariate Analysis

4.1 Different Effects of First-wave and Second-wave Migration on Educational Performance

4.1.1.1 Results from DD analysis

For first-wave migration, we use models (1) - (4) of the DD estimator to examine the effect of migration on academic performance in six types of migrant households. Of these six types of households, we focus on the *any parent migrated* household treatment group that we discussed above. One of the most important findings from Table 4 is that first-wave migration does not significantly affect school performance. In all four models, the coefficient of the *any parent migrated* household dummy variable is negative but not statistically significant. For example, when we use the unrestricted and adjusted specification of the DD estimator (column 4, row 1), the magnitude of the coefficient is small, -0.01 SD, and is not statistically significant. This means that, everything else held constant, after any parent in a household out-migrated between baseline and endline surveys, the migration did not cause a significant decrease in their child's standardized math test scores.

For second-wave migration, the results from the DD analysis using models (1) - (4) are consistent with our hypothesis that second-wave migration has a relatively larger negative effect on school performance than first-wave migration. For example, when we use the unrestricted and adjusted specification of the DD estimator (column 4), the coefficient of the *both parents migrated* household 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 standardized math test scores decreased relative to the children of *one parent migrated* households. 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 R-square statistic) since it captures baseline scores as well as other covariates.

4.1.1.2 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 standardized math 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 6, column 4, row 1). In other words, the scores of our treatment group (*both parents migrated*) and comparison group (*one 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.

4.2 Heterogeneous Effects of Second-wave Migration on Educational Performance

While we found mostly negative impacts of second-wave 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. In this section we use model (5) to test the heterogeneous effects of second-wave migration along a number of variables. For brevity, we only report the results from the unrestricted and adjusted model.

The heterogeneous analyses show that the negative effect on LBCs is greater for oldest children and non-boarding students. The coefficient on the interaction term between the variable indicating *both parents migrated* households and a dummy variable for being the oldest child is -0.12 SD and significant at the 10% level (Table 7, column 1, row 8). This result means that the negative impact of the departure of the second parent on academic performance was significantly larger for oldest children than for other children. This result is consistent with the existence of a significant negative care effect, especially for those who may be most impacted by parental absence. 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. Indeed, previous studies have suggested that in migrant households older children are more likely to do household chores, and to spend longer doing them, than younger children (de Brauw and Mu, 2011).

The coefficient on the interaction term between the variable indicating *both parents migrated* households and a dummy variable for being a boarding student is 0.23 SD and is significant at the 5% level (Table 7, Column 1, row 6). This result means that the negative effect of the departure of the second parent on academic performance was significantly larger for non-boarding students than for boarding students. For boarding students, boarding at school may actually offset the negative impact of the final parent's out-migration. For non-boarding students, however, grades decrease when the final parent out-migrates. These results confirm the existence of the care and income effects. For boarding students, who already live away from their parents, the migration of the second parent provides a pure positive income effect without the negative effect of decreased care, likely because the children are being cared for by other adults at the school's boarding facilities. For non-boarding students, who live at home without parental supervision, the negative effect of the decrease in parental care predominates. As shown in Table 7, we find no significant evidence of heterogeneous effects for other student demographic and family characteristics.

4.3 Results of Multivariate Analysis of Qinghai Sample

As an additional test of how the effects of first and second-wave migration on academic performance differ, we look at the data set examined by Bai et al. (2015), who found a net positive effect of parental migration on student academic performance. The sample was described in Section 2. We reproduce a table of results from their paper below (Table 8). Bai et al. analyzed first-wave migration in this paper. For *Any Parent Migrated,* the point estimate of the unrestricted and adjusted specification is 0.04 SD, which is significant at the 5% level.

We then conduct an original analysis of the effect of second-wave migration on this sample, using different treatment and control groups than Bai et al. did in their original analysis. The results are in Table 9. We focus on column 4 of Table 9, the coefficient for our *both parents migrated* treatment group using the unrestricted and adjusted DD specification. The point estimate is 0.00, which is not statistically significant. Although this coefficient is not negative (as it was when we examined second-wave migration in Shaanxi), it is significantly lower than the 0.04 SD estimate for first-wave migration. Thus, we find that the effect of migration on academic performance is less positive for second-wave than for first-wave migration in Qinghai, consistent with our findings from Shaanxi.

While we cannot fully explain why the effect of first-wave migration differs between Qinghai and Shaanxi, we believe it could be related to the different income levels in the two provinces. The average annual income in Qinghai is 7,295 RMB (1,109 USD) lower than that in Shaanxi. Du et al. (2005) found that migrants from poorer families tend to remit higher shares of their incomes, so it is possible that the per-dollar effect of migrant income on education is larger in Qinghai than in Shaanxi. Thus, the income effect is able to more than offset the care effect for first-wave migration in Qinghai. However, since the income effect is less salient in second-wave migration as children likely receive some increase in remittance income but lose all parental care, that net positive effect disappears. For second-wave migration in Qinghai, the income effect only just offsets the care effect.

4.4 Heterogeneous effect of Qinghai results

In Qinghai, the heterogeneous analyses show that the effect of second-parent migration on grades is more positive for students who are members of ethnic minority groups (Table 10). The coefficient on the interaction term between the variable indicating *both parents migrated* households and a dummy variable for being in an ethnic minority group is 0.15 SD and significant at the 5% level (Table 10, column 1, row 3). For non-ethnic minorities, the impact of the final parent out-migrating is approximately zero, but it becomes significantly more positive for ethnic minorities. Ethnic minorities are generally poorer than Han Chinese (Yang et al., 2015). Even though there is a negative care effect from second-wave migration, it seems to be outweighed by the positive income effect, likely because these poorer ethnic minority children may not yet have adequate educational resources. As shown in Table 10, we find no significant evidence of heterogeneous effects for other student demographic and family characteristics.

4.5 Discussion

Why is it that first-wave migration does not have a significant negative effect on the scores of migrant children while second-wave 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-wave migration and second-wave migration. This may occur for several reasons. First, the remaining parent leaving the home causes the children in second-wave 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 (De Brauw and Mu, 2011; Chang et al., 2011). Thus, we expect that the negative effect of decreased parental care is typically greater when the final parent leaves the home than when a first-wave parent out-migrates.

Second, for first-wave 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., 2015). It may be because of the positive impact of this income that first-wave migration does not have a significant negative effect on school performance. For second-wave migration, the additional remittance income may have a smaller marginal impact on education achievement than the remittance income from first-wave migration (Taubman, 1989; Edwards and Ureta, 2003; Du et al., 2005). Combined with the potentially more negative effect of decreased parental care for second-wave migration, a smaller positive income effect may change the balance between the parental care and income effects for second-wave migration, making the net effect on academic performance more negative than in first-wave migration.

So what evidence is there that this is what is happening? Using our data, we can find several pieces of information that the income and parental effects differ for first-wave and second-wave migration. First, we have shown in both Shaanxi and Qinghai that second-wave migration has a more negative effect than first-wave 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 hypothesized, 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 Qinghai, the heterogeneous analyses show that the effect of second-parent migration on grades is more positive for students who are members of ethnic minority groups. Ethnic minorities are generally poorer than non-ethnic minorities (Yang et al., 2015). As we expected, then, the income effect is stronger for poorer groups, such as first-wave migrants who have not been receiving remittance income.

In addition to the evidence presented above, two further sources also demonstrate that the impact of second-wave migration on grades is more negative than that of first-wave migration. First, when we perform a DD analysis to compare grades from the pre-baseline survey conducted in February 2011 (used in the placebo test) with the grades from the baseline survey (used in our main analysis) we find that the point estimate decreased 0.05 SD between first-wave (*any parent migrated)* and second-wave migration (*both parents migrated*), though the coefficients on neither first-wave nor second-wave migration are statistically significant (Appendix Tables 1, 2). Second, while they only use the DD results as a preliminary analysis and do not focus on second-wave migration, Zhang et al. (2014) show that second-wave migration has a more negative impact on student grades than single-parent first-wave migration for both Math and Chinese. These negative impacts are consistent with all of our previous results and support our finding that second-wave migration has a more negative impact on academic performance than first-wave migration.

Our finding that the trade-off between the income and parental effects is weighted differently for first-wave and second-wave migration draws into question the results of previously published studies. While Bai et al. rejected “the hypothesis that migration negatively affects school performance”, we show, using their data, that we can only reject this hypothesis for first-wave migration, not for second-wave migration or parental migration, in general. Since their sample included 764 households in the first-wave migrant treatment group and 528 households in the second-wave migrant treatment group, this is an important distinction. 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-wave and second-wave migration, a distinction that we have shown matters. At best, these studies can only provide an average of the impacts of first- and second-wave migration, and so their results might differ solely because the proportion of first-wave migrant parents to second-wave migrant parents differed in their samples. In short, previous studies have applied their results too widely, claiming that their results held for all types of parental migration when they neglected to consider the effects of second-wave migration.

5. Conclusion

In this paper, we have tried to understand how the second wave of parental out-migration affects the academic performance of LBCs, and how this impact differs from that of the first wave of parental out-migration. For first-wave 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 standardized math scores before and after the second wave of parental 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-wave 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-wave migration. When the final parent migrated, the student lost his or her remaining parental care. This may not only increase the student's domestic responsibilities, but also prevent parents from being able to review his or her homework. Thus, student academic performance decreased more in second-wave than in first-wave migration. The Qinghai sample also shows the same more-negative effect of second-wave migration than first-wave migration.

Through heterogeneous analysis, we also find that second-wave 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. Additionally, we find the effect of second-wave migration is less negative for members of ethnic minority groups in areas of high ethnic minority concentration.

In light of our findings, we believe policy makers should take action to help improve the situation of LBCs. One possibility is implementing and designing an informational campaign in conjunction with a conditional cash transfer (CCT) program. 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 stay at home. 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, which is often the mother, stays at home. Given the high cost of the above method, we want to find an effective and low-cost solution. Ultimately, reform of *hukou* policy could alleviate the negative effects of parental migration on the academic outcomes of LBCs. Because of China's *hukou* household registration system, migrant children still retain their rural *hukou* status and unable to attend urban public schools (Lai et al., 2014). If the *hukou* registration system were reformed, migrant children would have urban *hukou* and be able to attend public schools. Living with their parents in urban areas, children could benefit from the income effect without any negative parental care effects. Subsequently, they would have a brighter future than if they were left at home.

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. We hope that, in the future, researchers will further examine the impact of second-wave migration on the lives of LBCs.

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