The Effect of Migration on Children's Educational Performance in Rural China

Abstract

Migration is widely known as one of the main ways of alleviating poverty in developing countries, including China. However, migration itself is not costless. In recent years, there is an emerging concern about the effect of migration on the educational achievement of the children of migrants in China since most of the young children of school age of the migrants are being left in the village when one or both of their parents move to the city to work. This paper examines the effect of the migration activities of the father and/or mother on the educational performance of elementary school students (First to Fifth grade). With a dataset that collected from a survey designed specifically to examine changes in school performance of children before and after their parents left the village to migrate to the city we use Difference-in-Difference and, propensity score matching approaches. Although the grades of the children from some migrants family are sometimes lower than those from non-migrants family (in the time period before and after migration), somewhat surprisingly, we find that there is no significant negative effect of migration itself on the children's school performance. In fact, in some cases (e.g., after the father migrates), performance improves. Our paper also demonstrates and explains the interaction effects of migration from wealth and household composition.

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The Effect of Migration on Children's Educational Performance in Rural China

Migration is widely known by economists and policy makers as one of the main ways of alleviating poverty in developing countries (Todaro, 1985). There are many positive effects. Having a migrant may increase a household's income per capita significantly (Du and Park, 2006). Migrant income helps reduce inequality (Benjamin et al., 2005). Increases in out-migration lead to investment in assets related to agricultural production (deBrauw and Giles, 2005).

Migration itself, however, is not costless. In recent years there is an emerging concern internationally about the effect of migration on the educational achievement of the children of migrants (Kandel and Kao, 2001; Edwards and Ureta, 2003; Cordoba, 2004; Yang, 2005; Hanson and Woodruff, 2003; McKenzie and Rapoport, 2005). In the first wave of migration in a country, many new migrants leave their children in the countryside in the care of others (Wu et al., 2004). If parental absence as a result of migration translates into less parental input into the education acquisition process, a migrant household may find that the educational attainment of its children is depressed (McKenzie et al., 2006).

As in the rest of the world, this is an important and emerging issue in China. It is well documented now that migration is rising fast, surpassing 100 million individuals (deBrauw et al., 2002). Migrants also are moving further away from home and leaving for a longer period of time (Rozelle et al., 1999). Since most of China's migration is by individuals instead of entire households, in most cases the school-aged children of the migrant parents are being left in the village when their fathers, mothers or both parents move to the city for work. Several researchers have claimed—albeit without any empirical backing—that school performance of the migrant children is being adversely affected (Wang and Wu, 2003; Tan and Wang, 2004; Li, 2004; Zhou and Wu, 2004).

If it is found that there is such an adverse effect and that the cost is high, the government may want to respond. For example, it might be possible to allocate funds to build boarding schools, implement mentoring programs, provide students with closer monitoring (e.g., through smaller class sizes) and/or build more schools in urban areas that welcome the children of migrants. Or the government could start to modify the educational policy to favor children of migrant households (Heckman, 2005). However, all of these will be expensive and these programs themselves will have costs.

On the other hand, if the costs that may be caused by the negative impacts of migration on the education attainment of the children of migrants are not that high—and there are several reasons to believe they may not be—then it may be that policy makers can avoid spending time and effort in producing a costly response (and use their freed up resources in other more needy areas). It may be that the children of migrant households are not hurt performance-wise when one or both of their parents leave. It could be that the children of migrant households perform more poorly, not because their parents leave, but that their grades were systematically lower to start with (Ye et al., 2006). In fact, because school performance may be tied to income (Blau, 1999; Korenman et al., 1995; Duncan et al., 1994; Hanushek, 1992; Wolfe; 1981) and migration may generate higher incomes (Du and Park, 2006), it could be that the children of migrants benefit due to the income effect from migration. In addition, there may be other effects that are masking the true relationship as well. Somewhat surprisingly, little work has been done to understand whether or not migration hurts the educational performance of children.

The overall goal of this paper is to examine the effect of migration activities of men and women on the educational performance of their children. It is possible that a better understanding will provide policy makers with the information they need to make (or not make) changes to the school system and childcare systems in China's rural and urban areas. To meet this goal, we will pursue three specific objectives. First, we compare the distribution of children's scores for different types of rural households—looking at the grades of the boys and girls from the migrant households and non-migrant households and describe how the grades vary over time. Second, we examine whether migration negatively affects the school grades of rural children. Third, we explore how migration will affect children's educational performance in different types of households, households that differ in terms of wealth or demographic composition.

To meet these objectives, we will rely on a set of data that we collected in 2006, a data collection effort that was designed specifically to examine changes in school performance of children before and after their parents left the village to migrate to the city. With this data set, we focus our attention on two types of households: the migrant households and the non-migrant households. The non-migrant households are those in which neither parent migrated during the study period. We divide migrant households into six types of households, the categories of which are defined to reflect who outmigrated (father and/or mother). Using these different subsets of groups of households, we compare the grade distributions and changes in grade distributions using non-parametric analysis. The descriptive analysis is supplemented by a more rigorous multivariate analysis on the determinants of children's educational performance using several approaches, including a Difference-in-Difference approach (DD), propensity score matching (PSM) and a combination of these two approaches (DDM). Finally, by using interaction terms in our DD framework we are able to understand if there is a greater, lesser or equal effect of migration on students from households with different wealth levels, and/or from households with different numbers of siblings.

This study is unique in several respects. First, it contributes to the limited understanding of the effects of migration on rural human capital investment by examining how children's grades correspond to the migration decisions of their parents. To date the literature on migration and human capital investment in origin communities is relatively small and is focused largely on the impact of migration on educational attainment (see, for example, Edwards and Ureta, 2003; Cordoba, 2004; Yang, 2005; Hanson and Woodruff, 2003; McKenzie and Rapoport, 2005). Second, our paper utilizes panel data from a survey designed specifically to examine changes in school achievement of children before and after their parents left the village to migrate to the city, a strategy that will help to eliminate some of the statistical problems that are associated with this type of analysis. Most of current research in China only uses cross sectional data. Third, we try to use the most up-to-date evaluation methods, instead of the more traditional OLS approaches.

There are limitations, however, in our approach. For example, we focus on students and their families from one small, poor part of China, a fact that limits our ability to say anything about China in general. In addition, since we sample from the population of children that made it to the sixth grade in rural schools, we ignore those that drop out and/or those that accompanied their parents to the city. According to information from the school sections of our survey work, the drop out rate in our sample is low. More than 98 percent of the children that started first grade were still in school in the sixth grade.

Data

The data used in this paper come from a survey executed by the authors in 2006. While the survey in part relied on recall data—especially for some of the control variables—we were able to use records and rely on multiple sources of information for our two key variables—grades of school achievement and migration status.

The sample was drawn from 36 primary schools in 12 towns in Shaanxi province, one of the nation's poorest provinces in northwest China. The sample was drawn using a multi-stage, clustering design with random selection procedures employed at each stage. In the first stage, six counties were selected from 93 counties in Shaanxi province. In the second stage, the survey team randomly selected two townships in each county. The two townships were chosen from a list of all townships in the county that were ranked according to per capita income. One township was chosen from relatively rich townships and the other from relatively poor townships. In stage three, a list of all primary schools was created in each township (where schools were limited to all primary schools that included six years of schooling—or all *wanxiao*). From this list three primary schools were chosen randomly.

The sample students were selected during the final stage of the sampling. The sample included all students that were in the entering year of the sixth grade classes in each of the sample schools. On average, there were 1.4 sixth grade classes per school, ranging from one to three. Being done in September, the students had just begun a new school year. Therefore, all of the sample students had just completed the fifth grade about two months previously (as the school year in China runs between early September and mid-July). In total, the sample included 1649 children and their families. Approximately 45 percent of sample students were girls. The ages of the students ranged between 10 and 16.

We also elicited information about the students from their homeroom teacher (or *banzhuren*). In more than 90 percent of the cases, the homeroom teacher had been with the students in his/her homeroom class for at least two years. In China the homeroom teacher not only teaches the children one or two subjects, he/she also is in charge of administering each students' school program and is the interface between the students and the principal's office and the students and their parents. Many homeroom teachers make a point of visiting the homes of their students. Therefore, in most cases the homeroom teach was intimately familiar with the school performance and family life of each student.

Our main measure of education achievement is based on the math and Chinese language scores of the students from 2001/2 (their first grade year) to 2005/6 (their fifth grade year).[1] Fortunately, in China every student in most every elementary school (including, at least, all of the schools in our sample) keeps in his/her possession a booklet that contains a comprehensive record of the math and Chinese scores for each semester of his/her schooling. This means that the school performance variables that we use in our analysis are record-based. In other words, the information on school achievement is not from recall, but is from each student's grade booklet. The grades were copied by our enumerators with the assistance of the homeroom teachers.

In this paper, we focus on second term (or spring semester) math and Chinese language scores because the scores for these classes are based on a single yearend test that is standardized. The exams are standardized in two dimensions. First, the questions are the same for all students within the schools in the same township. Second, the final exams were graded according to a single set of criteria by a township-wide panel of teachers.

In our analysis, we also primarily look at changes between the second term scores from the first and fifth grades. To check the sensitivity of this assumption, we also performed a great deal of sensitivity analysis. For example, we used average grades for the whole year instead of just for the second semester. In another alternative, we compared scores that averaged scores from first AND second grade from scores that averaged scores from fourth and the fifth grade. In each of these cases there were no substantive differences in our findings.

We also collected detailed information on the migration histories of each of the families. The first set of information came from the survey form that was collected from the students and their family. A form was filled out that asked for the migration status of each parent during the first grade and the migration status of each parent during the fifth grade. If the parents were both out of the village, in about 95 percent of the times were called one of the parents and asked them over the telephone. The homeroom teacher then was asked to verify the information. If there was any question about the validity of the information on the survey form, we attempted to reconcile the information by making a follow up query of the family. If the homeroom teacher was not present during the first grade, we consulted the personnel in the office and consulted information on the attendance of parents at parent-teacher meetings that are held during each term as a way of cross checking the information on migration status.

In this study we will focus on two types of households: *Migrant households* (or those households in which at least one parent outmigrated in 2002 and 2006) and non-migrant households. Recognizing that the effect of migration on student performance may be affected by who in the household outmigrates (that is, father/mother/both), we subdivided the Migrant households into six types of households: *Any Parent Migrated* households (that is, households in which both parents lived at home in 2002 and at least one parent –either the father; mother or both parents—outmigrated in 2006); *Father Migrated Only (or mother-stayed-at-home)* households where only the father outmigrated in 2006 but was at home in 2002; *Father Migrated (Unconditional*) households where the father was at home in 2002 but outmigrated in 2006 (including households in which the mother was either at home or not at home in 2006); *Mother*

Migrated Only (or father-stayed-at-home) households where only the mother outmigrated in 2006 but was at home in 2002; *Mother Migrated (Unconditional*) households where the mother was at home in 2002 but outmigrated in 2006 (including households in which the father was either at home or not at home in 2006); and *Both Parents Migrated* households where both parents were at home in 2002, but outmigrated in 2006. 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 labor force in 2002, households which are ignored in our study. In addition, for the non-migrant households, we define *Never Migrant* households as those where both parents stayed at home in both 2002 and 2006.

In addition to school performance and migration, a set of other questions were asked during the survey as control variables and which are used to create variables that can explore the heterogeneous effects of migration on school performance.[2] Specifically, as family wealth may improve the learning outcomes of students (Brown and Park, 2002), we asked the parents if their house was worth more than 5000 yuan or not as a proxy for their family's wealth.[3] Although this is a crude measure of wealth, we discovered that such a question is typically measured with fairly small error and eliminated the need to implement a long questionnaire to collect comprehensive information on income, assets and/or consumption. Finally, since many studies have also documented the effect of the number of children in a family and the scholastic performance of each child (Hanushek, 1992; Nuttall, 1976; Steelman and Mercy, 1980), we collected information on whether a student had any siblings or not.

Migration and Educational Performance

Similar to many rural regions in poor areas of China (see for example, Rozelle et al., 1999), many households in our sample were in the migrant labor force in 2002, the first year of our sample. In 2002 of the 1546 households in our sample (all of which had a child in the fifth grade in 2006), at least one parent outmigrated in 236 households, or from about 15 percent of total households (Table 1, column 1). Of the 236 households, only the father outmigrated in 149 households, only the mother outmigrated in 18 households and both parents outmigrated in 69 households.[4]

Also similar to the rest of China (as reported in deBrauw et al., 2002), the number of new migrant households rose fast during the study period. Of the 1,358 households that were not outmigrating in 2002 (column 1, row 4), at least one of the parents in 220 of these households entered the migrant labor force between 2002 and 2006 (row 4, column 2 – 4). After accounting for the 2002 migrant households that returned to the village (there were 81 such households—55+9+17— row 1 – 3, column 5), in 2006 at least one parent in 24 percent of the sample households (or 232+49+94=375/1594, row 5, column 2 – 4) was in the migrant labor force. Of all of the households, 1,138 were Never Migrant households. In the rest of the analysis—both descriptive and multivariate—our main comparisons will focus on the grade performance of the children of the 1138 Never Migrant households and those of the 220 New Migrant households.

If one were naively to visit rural areas and search out migrant parents (especially those households in which both parents outmigrated) and ask them the record of their child's school performance, it is possible to understand how the findings of such an inquiry could raise concerns about the impact of migration on school performance. In such an interview, one would likely have found that the grades of the fifth grade student of the New Migrant household would have fallen since the first grade. However, such an interpretation may not be an indication of a problem that can be blamed on migration. As our data show, it is not only the grades of the students of the New Migrant households that fell, but also the average grades of all children fell.

(Figure 1). A simple test also shows that means of scores in 2002 and in 2006 are significantly different. When asking teachers about this trend we were told the pattern of falling grades is easy to explain for both New Migrant and Never Migrant households: Fifth grade teachers grade a bit harder than first grade teachers and teach a more rigorous curriculum. As seen in Figure 1, this is true for both Math and Chinese classes.

If the interviewers had sought out households in which either both parents outmigrated or households in which only the mother outmigrated, the results of interviewing these households may have been an alternative source of concern about the effect of migration on the grades of the children of new migrants. As in the findings of a number of research teams (for example, Wang and Wu, 2003; Tan and Wang, 2004; Li, 2004; Zhou and Wu, 2004), in our sample the students of Both Parents Migrated households on average had lower average test scores during their fifth grade year than those from Never Migrant households (Figure 2). Although the difference is not statistically significant, the grades of the children of Only Mother Migrated households in 2006 were also lower than those of Never Migrants. While we will explore this result further in the analysis below, it may be that it is these types of findings, which appear in our 2006 data of a cross section of fifth grade households that has made the effect of migration on school achievement a high profile issue. Interestingly, if the interview team had chosen a Only Father Migrated household, they would have found that on average the grades of their children were slightly higher than those of Never Migrant households. Differences among different types of households are one part of the evidence that should caution those that are relying exclusively on cross sectional data that the issue of the effect of migration on school performance may be complicated and that care needs to be exercised in any interpretation.

The need to exercise caution is reinforced when comparing the distributions of scores and the changes in the distributions of scores from 2002 to 2006 between the students from Both Parents Migrated households and Never Migrant households (Figure 3). Although the scores of fifth grade students from Both Parents Migrated households scored lower than those from the Never Migrant households in 2006, they also scored lower in 2002 when the students were in the first grade. In other words, at least on average (and without holding other things constant) the grades of the students were already low in Both Parents Migrate households *before the parents migrated*. In fact, although it is difficult to tell definitively, by just reexamining Figure 3, one might actually infer that migration helps, and not hurts grades because it appears as if the gap between the scores of migrant children and non-migrant children actually was narrowing slightly between 2002 and 2006. Importantly, although there are differences in the point estimates in 2002 and 2006 between new migrants and never migrants, t-tests of the differences between the distributions in the panels for 2002 and 2006 in Figure 3 show that the means of the two distributions in each year are not statistically significant.

Further analysis of our data reveals that the determinants of school performance are complex and there are many factors that may explain why some students perform better than others. In other words, the fact that many other things are changing over time and differ between migrant children and non-migrant children may be masking the relationship between migration and grades. For example, as seen in Figure 1, grades change over time. In addition, grades differ by the amount of wealth—or more specifically, the value of the housing assets of the household.[5] Students from wealthier households score systematically higher than those from the poorer households (Figure 4, Panel A). This relationship in our data, in fact, is consistent with those found by others that have found that the grades of children from better off families often are higher since the children from these households have access to better nutrition and better studying facilities, including access to extra reading materials and exercise books (Princiotta et al., 2006). And the students from wealthier households also may have less housework to do as well so that they may spend more time on their study, which might also lead to higher scores than their less wealthy counterparts who may be asked to help out more around the house as families try to scratch out a living.

In addition, grades differ among households with different household demographic compositions. Students from the households in which there are no siblings scored slightly lower than those from the households with siblings in 2006 (Figure 4, Panel B). Such a finding is consistent with Brown and Park's study (2002), which found that children with older siblings have significantly higher test scores than their peers. It is possible that the grades of these children are higher because students without any siblings are unable to receive help from their siblings or because they have no siblings that they can share the burdens of household duties together.[6] If either a household's wealth or demographic composition differs systematically with a household's migration status—which is plausible—simple correlations between a family's migration status and the grades of its children could be misleading. For example, Giles and deBrauw (2006) find that migrant households, while poorer, improve their family's income status after migration. The change of income could have a positive effect on the grades of migrant children over time that might offset any other adverse impact. Therefore, further analysis needs to explore the impacts of migration on educational achievement while holding as many other factors constant as possible.

Methodology

The objective of this study is to examine the effects of the migration activities of parents on children's educational performance. In order to evaluate the effects of migration, migration is considered as the treatment and our sample households are divided into a treatment group and a control group. The treatment group includes all the New Migrant households. The control group includes all the Never Migrant households. With this set up, we are interested in understanding the mean impact of "treatment on the treated" which is the average impact of migration among those treated (Smith and Todd, 2005):

$$TT = E\left((Y_1 - Y_0) \mid X, D = 1\right) = E\left(Y_1 \mid X, D = 1\right) - E\left(Y_0 \mid X, D = 1\right) \qquad (1)$$

where we denote Y_1 as the outcome (student grade in our case) if the student is from New Migrant households, Y_0 as the outcome if a student is from Never Migrant households, D=1 stands for the group of households who migrated in 2006 for whom Y_1 is observed, D=0 stands for those who did not migrated in 2006 for whom Y_0 is observed. In reality we do not observe the counterfactual mean, $E\left(Y_0 \mid X, D = 1\right)$, or the mean outcome for the migrating households had they not migrated in 2006. Therefore, we employ a difference-in-difference method (DD) to compare the outcomes before and after a migration status change for households affected by the change (children in New Migrant households) to households not affected by the change (those from Never Migrant households).[7] In equation (1) Let t and t' denote time periods after (2006) and before (2002) the change of migration status. The standard DD estimate is given by:

$$DD = \left[E(Y_t \mid D = 1) - E(Y_{t'} \mid D = 1)\right] - \left[E(Y_t \mid D = 0) - E(Y_{t'} \mid D = 0)\right] \qquad (2)$$

The idea of using a DD estimator to produce DD estimates is that it allows us to correct the simple differences before and after for the treatment group (or New Migrant households) by subtracting the simple difference for the control group (Never Migrant households). By comparing the before-after change of treated groups with the before-after change of control groups, any common trends, which will show up in the outcomes of the control groups as well as the treated groups, get differenced out (Smith 2004).

In addition to the standard DD estimator, we implement three other DD estimators: an "unrestricted" version that includes $Y_{t'}$ as a right hand variable, an "adjusted" version that includes other covariates in addition to the treatment variable (in our case they are a series of control variables from 2002 or the pre-program period), and an unrestricted/adjusted model that combines the features of both the "unrestricted" and "adjusted" model. The unrestricted and adjusted DD estimators relax the implicit restrictions in the standard DD estimator that the coefficient associated with $Y_{t'}$ (pre-program outcome) and covariates in t' (pre-program period) equals one. The combination of unrestricted and adjusted DD estimators relaxes both of these assumptions. In summary, the models to be estimated are:

Model (1), Restricted & Unadjusted: $\Delta Score_i = \alpha + \delta MIG_i + \varepsilon_i$

Model (2), Unrestricted & Unadjusted: $\Delta Score_i = \alpha + \delta MIG_i + \gamma Score\_02_i + \varepsilon_i$

Model (3), Restricted & Adjusted: $\Delta Score_i = \alpha + \delta MIG_i + \beta X_i + \varepsilon_{i,}$

Model (4), Unrestricted & Adjusted: $\Delta Score_i = \alpha + \delta MIG_i + \gamma Score\_02_i + \beta X_i + \varepsilon_i$

where, i is an index for the student, $\Delta Score_i$ is the change of the second term score of student i between 2002 and 2006 (that is the final grade from the fifth grade minus the final grade from the first grade); MIG_i is the treatment variable (which makes δ the parameter of interest). In our analysis, we have six different treatments, namely: Any Parent Migrated households; Father Migrated Only households; Father Migrated (unconditional) households; Mother Migrated Only households; Mother Migrated (unconditional) households; and Both Parents Migrated households and estimate six different δ's. Finally, the term $\mathbf{X}_i$ is a vector of covariates that are included to capture the characteristics of students, parents and households. Throughout our analysis, $\boldsymbol{X}_i$ also includes a set of 12 town indicator or dummy variables.

It is important to remember that the identification of the causal effects using DD relies on the assumption that absent the policy change (or migration in our case), the average change in $Y_t - Y_{t'}$ would have been the same for the treated and the control groups. Formally, this is called the "parallel trend" assumption, which can be expressed as:

$$E(Y_{0,t} \mid D=1) - E(Y_{0,t'} \mid D=1) = E(Y_{0,t} \mid D=0) - E(Y_{0,t'} \mid D=0) \quad (3)$$

As might be expected, the effectiveness of DD depends on the validity of this assumption. Whether or not the assumption is valid, however, depends on the context of the study and on how similar the control and treatment groups are. In general, the more similar are the treatment and control groups, the more convincing the DD approach. Using our data we find that Never Migrant households (the control group) and Any Parent Migrated households (one of the treatment groups) are not significantly different in most respects in 2002 (Appendix A). This finding suggests that the parallel trend assumption may hold.

Alternative Estimation Approaches

Unfortunately, the reality of our question (understanding the effect of migration on the grades of children) may mean that even though we control for a large number of observable variables in 2002 in the adjusted and unrestricted versions of the DD estimates, there could be other unobservable factors that may compromise the parallel trend assumption. Because of the potential existence of other differences between Never Migrant and New Migrant households, we also use a series of propensity score matching methods (PSM) that is an approach that does not require the parallel trend assumption. PSM allows the analyst to match the treated and the controls when observable characteristics of Never Migrant and New Migrant households are continuous, or when the set of explanatory factors that determine participation contains multiple variables (Rosenbaum et al. 1985) With the right data, it is possible to estimate the propensity scores of all households and compare the outcomes of non-migrant and migrant households that have similar propensity scores.[8] We can obtain the mean impact of the treatment on the treated by (Dehejia and Wahba, 2002; Smith and Todd, 2005):

$$E(Y_1 - Y_0 \mid D=1) = E(Y_1 \mid D=1) - E_{Z|D=1}\left\{E(Y_0 \mid p(Z), D=0)\right\} \qquad (4)$$

where $p(Z) \equiv \Pr(D=1 \mid Z)$ is the propensity score. Matching is based on the assumption that outcomes (Y_0, which is student grades in our case) are independent of participation (migration) conditional on a set of observable characteristics (Rosenbaum and Rubin, 1983). So we do not need to worry about unobservable heterogeneity. By matching New Migrant households with Never Migrant households with similar values of $\Pr(D=1 \mid Z)$, any differences in $E(Y_0)$ between the two groups are assumed to be differenced out when calculating the above equation. The assumption of matching is that $E(Y_0 \mid Z, D=1) = E(Y_0 \mid Z, D=0)$. The observable covariates Z should include the characteristics that determine migration. In our analyses, Z includes a number of variables including student, parent and household characteristics. We also include township fixed effects to control for unobservable factors at the township level that may affect migration.

To implement PSM successfully, however, the nature of the samples of New Migrant and Never Migrated households in 2006 must meet certain criteria and several other choices must be made. Importantly, the common support of the propensity scores for participating and non-participating households should be fairly wide. Intuitively, wide common support means that there must be a fairly large overlap in the propensity scores between the treated and control groups. In our sample, the common support is fairly wide[9]. This means that we can estimate the *average* treatment effect for the treated of a large portion of the sample.

Once we determine that PSM is feasible, we next need to choose the method of matching. In our analysis, we choose to use the nearest neighbor matching method with replacement. Following Smith and Todd (2005), we match on the log odds-ratio and standard errors are bootstrapped using 1000 replications. We also use a balancing test that follows Dehijia and Wahba (1999, 2002) that is satisfied for all covariates. The results of the balancing tests are available upon request.

While PSM is often used in program evaluations, it relies on a key underlying assumption: outcomes are independent of migration conditional on a set of observable characteristics. Formally, this assumption can be written as:

$$E(Y_0 \mid P(Z), D=1) = E(Y_0 \mid P(Z), D=0) \tag{5}$$

In other words, there would be no need to worry about unobservable heterogeneity. However, even though we control for unobservable differences at the township level using fixed effects when estimating the propensity score, there may still be systematic differences between the outcomes of Migrant and Never Migrated households. The systematic differences could arise, for example, because the household's decision to migrate is based on some unmeasured household characteristics. Such differences could violate the identification conditions required for matching (Smith and Todd, 2005).

To eliminate the bias due to time-invariant unobservable differences between New Migrant and Never Migrant households, we extend the cross-sectional PSM approach to a longitudinal setting and implement a difference-in-differences matching (DDM) strategy. With DDM we can exploit the data on the Migrant households in 2002 to construct the required counterfactual, instead of just using the data in 2006 (as is used in the PSM analysis). The advantage of DDM is that the assumptions that justify DDM estimation are weaker than the assumptions necessary for DD or the conventional PSM estimator. DDM only requires that in the absence of treatment, the average outcomes for treated and controls would have followed parallel paths:

$$E(Y_{0,t} \mid P(Z), D=1) - E(Y_{0,t'} \mid P(Z), D=1) = E(Y_{0,t} \mid P(Z), D=0) - E(Y_{0,t'} \mid P(Z), D=0) \quad (6)$$

Assumptions embedded in equation (6) are weaker than the assumptions necessary for DD. Intuitively, DDM removes time invariant unobservable differences between New Migrant and Never Migrant households conditional on P(Z), a clear advantage over cross-sectional PSM.[10]

In performing DDM we match by using the log odds-ratios and the same nearest neighbor matching methods with replacement that were used in our PSM approach (which were described above). In addition, we also compute the "adjusted" version where the control units are weighted by the number of times that they are matched to a treated unit. The standard errors also are bootstrapped using 1000 replications.

Although the above matching methods can significantly improve the reliability of matching estimators, producing results that have been shown to be very close to those based on a randomized design (Smith and Todd, 2005; Abadie and Imbens, 2006). Smith and Todd (2005) counsel that geographic mismatch between matched observations should be avoided. In our case, when we use PSM, even if we have added a set of township dummies when estimating the propensity scores, students that are from different townships but have similar propensity scores may still be matched as a pair of treatment and control observations. Abadie and Imbens (2006) propose a method to eliminate bias caused by imprecise matching of covariates between treatment and control observations using nearest neighbor matching. They also developed a formula to estimate standard errors for matching with a fixed number of nearest neighbors that are asymptotically consistent and which can accommodate unobserved heterogeneity in the treatment effect.[11] In this paper, we use the nearest neighbor matching algorithm with bias adjustment developed by Abadie and Imbens (2006).

In making specific choices about the methodology, our approach is to minimize potential bias whenever possible. To minimize geographic mismatch, we enforce exact matching by township.[12] Each treatment observation is matched to three control observations with replacement, which is few enough to enable exact matching by township for nearly all observations but enough to reduce the asymptotic efficiency loss significantly (Abadie and Imbens, 2006). When we use this method for matching, we report our results as *multi-dimensional matching* results to differentiate this approach to matching from the traditional or *basic matching* approach that we also use (and which was described above).

Matching is based on a set of covariates which are time-invariant or were measured in 2002. The weighting matrix uses the Mahalanobis metric, which is the inverse of the sample variance/covariance matrix of the matching variables. We chose a set of 11 matching variables (see Appendix A) for household level matching. Furthermore, we use the propensity scores as a diagnostic tool to restrict the sample used in each matching estimation to those with common support We also visually examined the graphs of the propensity scores and trimmed the sample if there was a large imbalance between control observations and treatment observations with similar propensity scores. This approach has been shown to prevent the estimates from relying too heavily on just a few control observations.

Results of Multivariate Analysis

The results of our DD analysis of Models (1) to (4) for the version of the 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 (Table 2). For example, when we use the Unrestricted and Adjusted specification of the empirical model (column 4), the scores of students that are older in the first grade drop relatively more than those of younger students (row 4). This finding is reasonable since, ceteris paribus, students that are older when entering elementary school may have an initial advantage (because they are relatively more mature) that gradually disappears as younger children catch up over the course of elementary school, which is consistent with other findings. For example, Fredriksson and Björn (2005) find that children who start school at an older age do better in school and go on to have more education than their younger peers. Additionally, when a student's mother has a higher level of education, the student's grades improve relatively more over time. While few papers in the literature have examined the impact of the mother's education on the *change* of grades, there is a large, related literature that shows the strong, positive correlation between mother's education and the school performance of her children (e.g., Duncan and Brooks-Gunn, 1997). Throughout our results, the results of the Unrestricted and Adjusted specification has a much higher goodness of fit (or R-square) statistic, in part reflecting the importance of capturing beginning grades (and the unobserved ability of a student that is embodied in this measure) and other covariates. Therefore, in the rest of the analysis, while we report the results from Models (1) to (4), we will mostly focus on the results from Model (4).

The most important finding in Table 2 is that we reject the hypothesis that migration negatively affects school performance. In all four models the coefficient on the Any Parent

Migrated household treatment variable is *not* negative (row 1). In fact, the coefficients are all positive and significantly different from zero (at least at the 10 percent level—as in column 4). The sizes of the coefficients range from 1.16 to 3.18, meaning that, everything else held constant, after any parent in a household (that is, father, mother or both parents) outmigrated between the first and fifth grade during the student's elementary school years, the grades of the children of the migrants actually rose relatively to the children of Never Migrant households. In other words, migration did not hurt school performance as some have feared, at least in the households of the migrants in our sample area, migration has improved school performance.

The same basic results hold when using any other measure of migration; there is no negative effect of migration—however defined—on school performance (Table 3). In Table 3 we only report the coefficients of the treatment variable (that is, δ). The rest of the results are suppressed for brevity but are available from the authors upon request. We report the results for 24 different regression models. For each of the four specifications (that are in each column) we separately look at the impact of migration on school performance using the six different measures of migration (or the six different treatment variables, one measure is reported in each row).[13] In 20 out of the 24 cases the coefficient is positive. In only four cases (in the cases of Mother Migrated Only households (row 4) and Mother Migrated Unconditional households (row 5) when using the Restricted & Adjusted (column 3) and Unrestricted & Adjusted models (column 4)) are the coefficients negative. In each of these four cases, however, the t-ratio is low (never more than 0.50), implying that there is no statistically significant effect of migration on school performance. Interestingly, as in the case of Any Parent Migrated households (Table 2 and Table 3, row 1), when the father outmigrates (in either Father Migrated Only households or Father Migrated Unconditional households) the grades of migrant children improve.

So why is it that migration does not appear to have a negative effect on the grades of migrant children, and in some cases appears to have a positive effect? Although we can not definitively say on the basis of the results of Tables 2 and 3, one possible reason is that the income effect is relatively large compared to the adverse effect of less parental supervision. If migration leads to higher income, as found in Du and Park (2006), the migrant families that experience rising incomes may be able to provide better nutrition, improved access to educational supplies and/or require their children to work less and this may have a positive effect on school performance. This is consistent with the finding that the largest positive effects among all of our models are found among households in which only the father migrates (Table 3, row 2). This result may arise since in such households not only would the children benefit from higher incomes from migration, they would also suffer relatively less from falling parental care since the mother is still at home. Such an interpretation also is consistent with other findings. For example, in Kandel and Kao (2001) it is found that when fathers of families migrate from Mexico to the US the grades of children in such families improve.

Propensity Score Matching (PSM) Results

The results of cross-sectional PSM analysis—regardless of the method of matching—also reveal that migration has no significant negative effect on the school performance of students. When examining the effect of migration on school performance for all six types of New Migrant households using Basic Matching methods, there are no cases in which the coefficient on the treatment variable is negative and significant (Table 4, column 1, rows 1a, 2a, 3a, 4a, 5a and 6a). The same is true when using Multi-dimensional Matching (rows 1b, 2b, 3b, 4b, 5b and 6b). In fact, the results from the PSM analysis are quite similar to those from the DD analysis. Although there are no positive and significant coefficients when we use Basic Matching, when we use Multi-dimensional Matching (likely the better method) we find that the coefficients on the treatment variables in the Father Migrated Only household model and Father Migrated Unconditional household model are positive and significant and the magnitudes are similar.

Finally, the findings continue to remain largely consistent when using Difference in Difference Matching (DDM—Table 4, column 2). Regardless if we use Basic Matching (rows 1a, 2a, 3a, 4a, 5a and 6a) or Multi-dimensional matching (rows 1b, 2b, 3b, 4b, 5b and 6b), none of the coefficients of the treatment variables are negative and significant. When using Multi-dimensional Matching, in the Any Parent, Father Migrated Only and Father Migrated Unconditional models, the coefficients are positive and significant. Hence, whether using DD, PSM or DDM, there is no evidence that migration in our sample of households has hurt school performance. In fact, we find that when the father outmigrates (either by himself or with others), migration appears to have a small, positive effect on the school performance of migrant children.

Heterogeneous effects

While we have found no significant negative impact of migration on the school performance of migrant children, all of these results have been for the *average household* (that is, for the typical migrant households). It is possible, however, that although on average there is no effect that there could be a negative effect on certain types of migrant households. In this subsection we examine whether or not migration affects households those: a.) are more or less wealthy; or b.) have an "only child" or more than one child. To do so, we use a modified specification of the basic four models, which are presented in Appendix B. For brevity, we only report the results of the Unrestricted & Adjusted, but the results are robust to this specification of the model.

Like the results for the average households reported in Tables 2 to 4, the results from DD analysis that examines the heterogeneity effects on less and more wealthy households demonstrate that there is no significant effect of migration on children from either poorer or wealthier households (Table 5, Panel A). The coefficient on the interaction term between the dummy variable for the less wealthy households and the migration variable is insignificant for all of the types of migrant households except for Any Parent Migrated households (rows 2 to 6). This means that there are no significant differences between less and more wealthy households. Since in no case is the coefficient on the migration variable negative and significant (in fact, they are all positive), this means that in the five cases there is no detectable negative effect for any type of household when looking at wealth categories. In the case of Any Parent Migrated households, although the coefficient on the interaction term is negative and significant (-2.27—column 1, row 2), the coefficient on the base migration variable is positive and significant and the magnitude is slightly larger (2.40—column 1, row 1). When testing the net impact of migration on less wealthy households, we can not reject the hypothesis that the net impact equals to zero (2.40 + -2.27 = 0—statistically, that is, we tested Any_Parent_Migrated+ Any_Parent_Migrated*Poor = 0). In short, there is no negative effect of migration on the children's school performance in either less or more wealthy households.

Similar to the results from panel A, the results from DD analysis that examines the heterogeneity effects on the grades of children from households with one child and households with more than one child reveal that there is no significant different effect (Panel B). The coefficient on the interaction term between the dummy variable for One Child households and the migration variable is insignificant (rows 1 to 6). Although children with older siblings may have significantly higher test scores than their peers (Brown and Park, 2002), when it comes to the interaction effect of household composition with migration, there is no statistically significant effect.

Summary and Conclusions

In this paper we have tried to understand whether or not the school performance of children suffer when their parents outmigrate. Despite a perception that is commonly found in the literature and the popular press, our results—somewhat surprisingly—show that there is no effect of the process of migration itself on the school performance of the children from migrant households. Comparing the change over time (between the first and fifth grade) of the grades of children from migrant households with those of children from households that did not migrate during the study period, we can reject the hypothesis that migration harms the grades of their children when their father, mother or both parents migrate from the village into the city. In fact, in the analysis of some migrant households (especially in those in which the father outmigrates) migration is shown to have a statistically significant and positive effect on the performance of migrant children. We also find that there is neither a systematically different effect of migration between the children of more wealthy and less wealthy households nor between the children from families that have one and more than one child.

Based on these results, it might be tempting to conclude that since there is no measurable effect of migration on school performance that policy maker do no need to take any actions. If there was, education officials might want to consider trying to improve the environment in rural schools so that that teachers could pay more attention to students in schools in which there were many children of migrants. This could be done by reducing class size or hiring more qualified teachers. Boarding schools might offer some of the services that parents originally carried out before they entered the migrant labor force. Ultimately, measures might be promoted the offered the children of migrants who lived in China's cities better access to urban schools so parents would not have to leave their children behind. However, all of these programs are expensive. And, although there might be good reason to implement such policies anyhow, according to a strict reading of our results, they should not be carried out because migration has a negative effect on school performance; at least in our study area there is no evidence that this is true.

Is there any reason to question the validity of our results and question such conclusions? Although we have tried a number of alternative approaches to identify the effect of migration, and although the findings are largely robust, in fact, we know that some of the assumptions of our methodologies may not be perfectly valid in the real world and that the coefficients could be measured with a degree of bias. Even though we control for many observed and unobserved effects, there still may be factors that are observed by the parents of migrants and potential migrants that can not be observed by the econometrician. For example (and most importantly), it may be that all parents who were in the village with their children in 2002 worry about whether or not their migration decision would negatively affect the school 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. The measured effect of migration on grades would not only be picking up the migration effect.[14]

If there was, in fact, 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 outmigrate, the grades of their children do not suffer. It is true that part of the reason for the zero effect may be exactly this selection effect—parents do not go when they believe the grades of the children would suffer. But, from society's point of view, there is no cost in terms of school performance of its children due to migration.

However, one believed that the selection effect was materially important, that does not mean that there is no cost to migration and it might call into question the implications of the model that we raised above—extensive investments are not needed to improve the mentoring and attention that children receive in schools that are attended by migrant families. In fact, it is the parents and the family as a whole that is paying the cost. The parent is forgoing a chance to outmigrate and forgoing the higher income and other benefits that come from migration. It is possible that if schools were restructured in rural areas so that they were more attentive to the needs of the children of migrants or in urban areas so that they were more welcoming, migration would rise and overall both the families—and society as a whole—would benefit.

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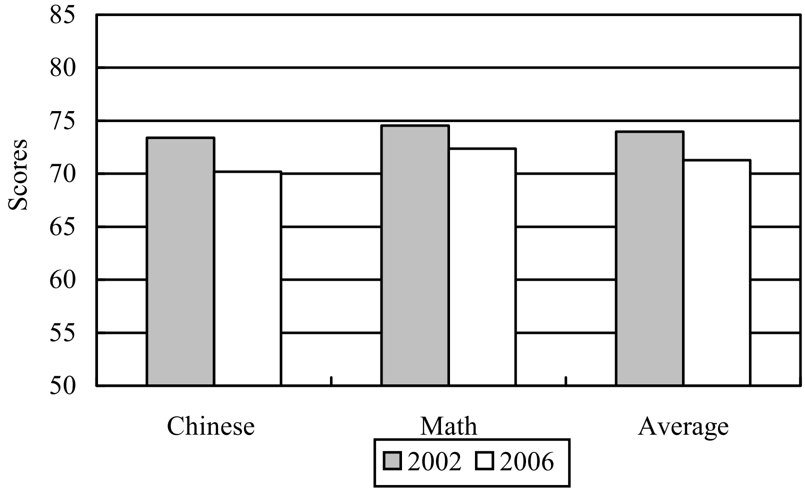

Figure 1. Average Yearend Test Scores in China, 2002 and 2006.
Data source: Authors' survey
Note: Scores are averages of sample test scores from standardized test scores for Chinese class; math class and the *average* of Chinese and math of students in 2002 (first grade scores) and 2006 (fifth grade scores).

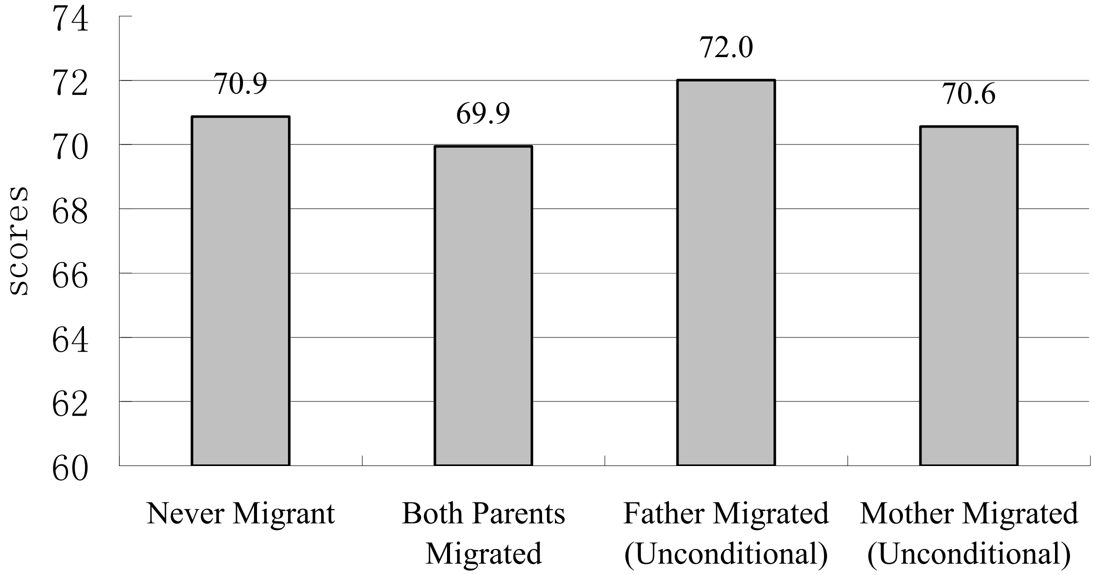

Figure 2. Differences in Yearend Test Scores between First Grade Students from Migrant and Non-migrant Households in Rural China, 2006.
Data source: Authors' survey
Notes:
Never Migrant stands for the students that lived in households in which both parents stayed at home in both 2002 and 2006.
Both Parents Migrated, stands for the students that lived in households in which both parents were at home in 2002, but outmigrated in 2006
Father Migrated (Unconditional) stands for the students that lived in households in which the father was at home in 2002 but outmigrated in 2006 (including households in which the mother was either at home or not at home in 2006).
Mother Migrated (Unconditional) stands for the students that lived in households in which the mother was at home in 2002 but outmigrated in 2006 (including households in which the father was either at home or not at home in 2006).

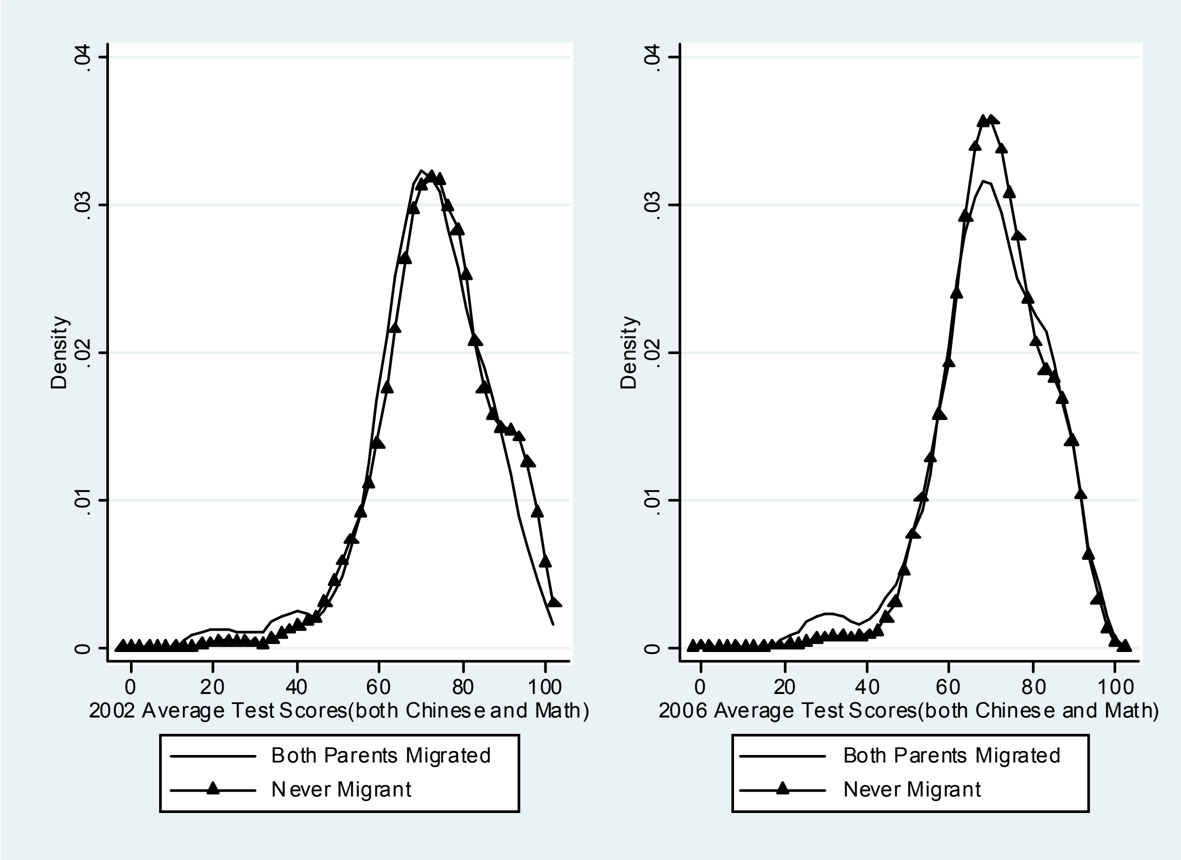

Figure 3. Kernel Density Plots of Distributions of Average Test Scores in Households in which Parents Never Migrated and in Households in which Both Parents Migrated in China, 2002 and 2006.

Data source: Authors' survey

Note: See Figure 2 for the definition of Never Migrant and Both Parents Migrated.

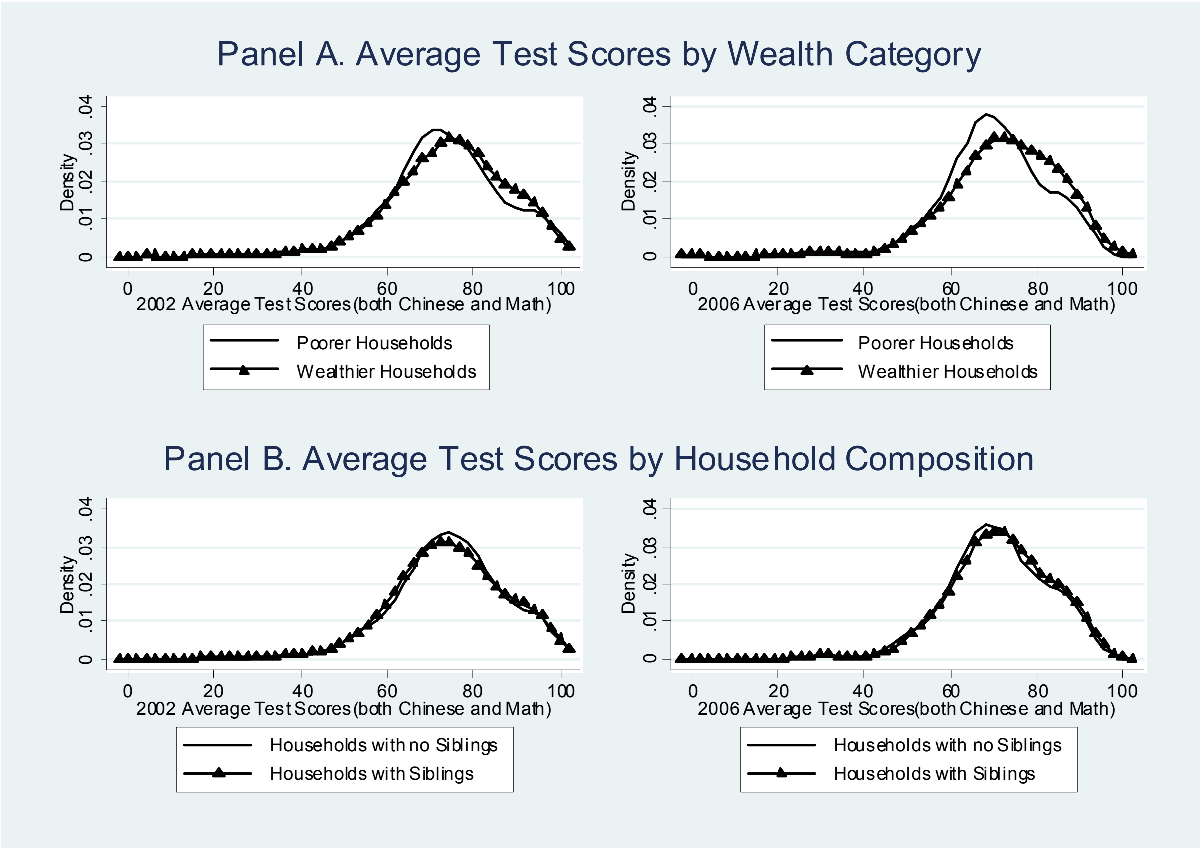

Figure 4. Kernel Density Plots of Distributions of Average Test Scores in Households that Vary by Wealth Category and Household Composition in China, 2002 and 2006.

Data source: Authors' survey

Note: *Poorer Households* are those in the lowest quartile of the sample in terms of self-reported value of the family's house; *Wealthier Households* are those in the upper quartile. *Households with no Siblings* are those in which the household's student is an only child; *Households with Siblings* are those in which the household's student has at least one brother or sister.

Table 1. Patterns of Migration for Sample Households in China, 2002 and 2006.

			Migration status in 2006			
		(1)	(2)	(3)	(4)	(5)
Migration Status in 2002		Number of Migrants/ Non-migrants in 2002 [a]	*Father Migrated Only (mother stayed home)*	*Mother Migrated Only (father stayed home)*	*Both Parents Migrated*	*Return migrants* (rows 1-3) / *Never Migrant* (row 4)
(1)	*Father Migrated Only* (mother stayed home)	149	94 [d]			55 [c]
(2)	*Mother Migrated Only* (father stayed home)	18		9 [d]		9 [c]
(3)	*Both Parents Migrated*	69	7	5	40 [d]	17 [c]
(4)	*New Migrants* (col. 2, 3 and 4) / *Never Migrant* (col. 5)	1358	131 [b]	35 [b]	54 [b]	1138
(5)	Total number of households	1594	232	49	94	1219

Data source: Authors' survey

[a] Column (1) = Column (2) + Column (3) + Column (4) + Column (5)

[b] Total new migrants (or those households in which the parents did not migrate in 2002 and did migrate in 2006) is found in row 4 by summing columns 2, 3 and 4).

[c] The households in column 5, rows 1, 2 and 3 are return migrants (or those households in which households had a migrant in 2002 and by 2006 had returned home. These households are dropped from the multivariate analysis.

[d] The diagonal elements in the first three rows of the 2006 matrix (row 1, column 2; row 2, column 3; row 3, column 4) are *Always Migrant* households. These households are dropped from the multivariate analysis.

Table 2. Difference in Difference Regression Results Analyzing the Effect of Migration on School Performance of Students in China.[a]

Dependent Variable = Changes in Second Term Test Scores between 2002 and 2006 ($\Delta Score$)		(1)	(2)	(3)	(4)
		Restricted & Unadjusted	Unrestricted & Unadjusted	Restricted & Adjusted[c]	Unrestricted & Adjusted[c]
Treatment Variable (MIG_i)[b]					
(1)	*Any_Parent_Migrated*	3.183	2.327	2.169	1.164
		(3.72)***	(3.03)***	(2.58)**	(1.65)*
Characteristics of the students in 2002					
(2)	Student score in the second term in 2002 (Full score is 100)		-0.460		-0.627
			(14.93)***		(18.04)***
(3)	Gender dummy (=1 if male and 0 if female)			0.826	-0.383
				(1.28)	(0.75)
(4)	Age of the student in 2002 (Years)			0.097	-1.322
				(0.26)	(4.39)***
(5)	Cadre dummy (=1 if the student was a student cadre in 2002 and 0 if not)			-2.754	1.168
				(3.83)***	(1.93)*
(6)	Mentor dummy (=1 if the student had a mentor in 2002)			-1.051	-0.972
				(0.99)	(1.26)
(7)	Sibling dummy (=1if the student had no siblings in 2002)			0.438	0.443
				(0.55)	(0.71)
Characteristics of the parents in 2002					
(8)	Age of the father (Years)			-0.066	-0.053
				(0.85)	(0.85)
(9)	Level of education of the father (Years of schooling)			-0.200	-0.044
				(1.06)	(0.35)
(10)	Level of education of the mother (Years of schooling)			0.114	0.274
				(0.77)	(2.39)**
Characteristics of the household in 2002					
(11)	Size of total household land holding in 2002 (mu)			0.031	0.037
				(0.36)	(0.57)
(12)	Number of household members in 2002 (Person)			0.078	0.251
				(0.25)	(1.01)
(13)	House value dummy (=1 if the house is worth more than 5000 yuan)			0.056	-0.037
				(0.08)	(0.07)
(14)	Number of Observations	1575	1575	1549	1549
(15)	R-squared	0.01	0.27	0.10	0.43

Data source: Authors' survey. Robust t statistics in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%

[a] The regression models used in this table are the following specifications respectively:
(i) Model (1): $\Delta Score_i = \alpha + \delta MIG_i + \varepsilon_i$; (ii) Model (2): $\Delta Score_i = \alpha + \delta MIG_i + \gamma Score\_02_i + \varepsilon_i$
(iii) Model (3): $\Delta Score_i = \alpha + \delta MIG_i + \beta X_i + \varepsilon_i$, (iv) Model (4): $\Delta Score_i = \alpha + \delta MIG_i + \gamma Score\_02_i + \beta X_i + \varepsilon_i$
Where, i is an index for the student, $\Delta Score_i$ is the change of the second term score of student i between 2002 and 2006; MIG_i is the treatment variable (so δ is the parameter of interest).
[b] In this table the treatment variable MIG_i is *Any_Parent_ Migrated*, a dummy variable that is equal to 1 if both parents lived at home in 2002 and at least one parent (either the father; mother or both parents) outmigrated in 2006.
[c] The coefficients of the township dummy variables are NOT reported here for the sake of brevity.

Table 3. Difference in Difference Regression Results Analyzing the Effect of Migration on School Performance of Students in China by Household's Migration Status [a]

	Treatment Variable (MIG_i)[b]	(1) Restricted & Unadjusted	(2) Unrestricted & Unadjusted	(3) Restricted & Adjusted[c]	(4) Unrestricted & Adjusted[c]
		Dependent Variable = Changes in Second Term Test Scores between 2002 and 2006 ($\Delta Score$)			
(1)	*Any_Parent_migrated,*	3.183	2.327	2.169	1.164
		(3.72)***	(3.03)***	(2.58)**	(1.65)*
	No. of Observations	1575	1575	1549	1549
	R-squared	0.01	0.27	0.10	0.43
(2)	*Father_Migrated_Only*	4.634	3.812	3.630	2.356
	(mother stayed home)	(4.27)***	(4.09)***	(3.45)***	(2.73)***
	No. of Observations	1577	1577	1549	1549
	R-squared	0.01	0.28	0.10	0.43
(3)	*Father_Migrated*	3.812	2.879	2.984	1.508
	(Unconditional)	(4.10)***	(3.52)***	(3.24)***	(1.98)**
	No. of Observations	1595	1595	1551	1551
	R-squared	0.01	0.27	0.10	0.43
(4)	*Mother_Migrated_Only*	0.839	0.156	-0.861	-0.121
	(father stayed home)	(0.45)	(0.08)	(0.45)	(0.07)
	No. of Observations	1576	1576	1549	1549
	R-squared	0.00	0.27	0.09	0.43
(5)	*Mother_Migrated,*	0.903	0.444	-0.147	-0.541
	(Unconditional)	(0.73)	(0.37)	(0.12)	(0.48)
	No. of Observations	1587	1587	1551	1551
	R-squared	0.00	0.27	0.09	0.43
(6)	*Both_parents_migrated,*	1.367	0.615	1.040	-0.536
		(0.79)	(0.38)	(0.58)	(0.35)
	No. of Observations	1575	1575	1549	1549
	R-squared	0.00	0.27	0.09	0.43

Data source: Authors' survey. Robust t statistics in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%

[a] See Table 2 for specification of regressions.
[b] The treatment variable MIG_i takes the following six forms:.
AnyParent_Migrated, which is a dummy variable that is equal to 1 if both parents lived at home in 2002 and at least one parent (either the father; mother or both parents) outmigrated in 2006.
Father_Migrated_Only(mother stayed at home) is a dummy variable that is equal to 1 if only the father outmigrated in 2006 but was at home in 2002;
Father_Migrated (Unconditional) is a dummy variable that is equal to1 if the father was at home in 2002 but outmigrated in 2006 (including households in which the mother was either at home or not at home in 2006);
Mother_Migrated_Only(Father stayed at home) is a dummy variable that is equal to 1 if only the mother outmigrated in 2006 but was at home in 2002;
Mother_Migrated (Unconditional) is a dummy variable that is equal to 1 if the mother was at home in 2002 but outmigrated in 2006 (including households in which the father was either at home or not at home in 2006);
Both_Parents_Migrated is a dummy variable =1 if both parents were at home in 2002, but outmigrated in 2006;
[c] The coefficients of the township dummy variables are NOT reported here for the sake of brevity.

Table 4. Propensity Score Matching and Multi-dimension Matching Estimators and the Effect of Migration on the School Performance of Students in Rural China, 2002 and 2006 [a].

Treatment Variable [c d]		Propensity Score Matching		Difference-in-Difference Matching	
		Average Treatment Effect for the Treated	t-value/ z-value [b]	Average Treatment Effect for the Treated	t-value/ z-value [b]
		(1)		(2)	
Any_parent_migrated	(1a) Basic Matching	1.16	(1.02)	0.31	(0.28)
	(1b) Multi-dimensional Matching	1.57	(1.60)	2.12	(1.86)*
Father_Migrated_Only (mother stayed home)	(2a) Basic Matching	2.04	(1.36)	1.12	(0.77)
	(2b) Multi-dimensional Matching	3.59	(2.96) ***	3.12	(1.93)**
Father_migrated, (Unconditional)	(3a) Basic Matching	1.57	(1.20)	2.35	(1.93)**
	(3b) Multi-dimensional Matching	2.19	(2.04) ***	2.52	(1.99)***
Mother_Migrated_Only (father stayed home)	(4a) Basic Matching	-0.63	(-0.22)	-1.1	(-0.39)
	(4b) Multi-dimensional Matching	-0.94	(-0.43)	1.93	(0.58)
Mother_migrated (Unconditional)	(5a) Basic Matching	-0.45	(-0.26)	-1.51	(-0.88)
	(5b) Multi-dimensional Matching	-0.46	(-0.32)	0.82	(0.48)
Both_parents_migrated	(6a) Basic Matching	-0.22	(-0.09)	-0.56	(-0.23)
	(6b) Multi-dimensional Matching	-0.28	(-0.13)	0.97	(0.43)

Data source: Authors' survey

[a] The method of nearest neighbor matching is used to get the Basic Matching results of propensity score matching and multi-dimension matching.

[b] t-values and z-values are reported in parentheses. t –values are calculated with the coefficient and standard errors got by Bootstrapping is used to obtain standard errors for the basic propensity score matching, and z-values are reported for the multi-dimensional matching. * denotes significant at 10% level, ** denotes significant at 5% level, * **denotes significant at 1% level,

[c] The covariates, X_i , used in generating the propensity score estimates are the same as those in Table 2.

[d] The treatment variables are described in the notes of Table 3.

Table 5. Difference in Difference Regression Results with Heterogeneous Effects from Wealth and Household Composition

Dependent Variable = Changes in Second Term Test Scores between 2002 and 2006 (*ΔScore*)				
Panel A *Heterogeneity Effects from Wealth*[a]			Panel B *Heterogeneity Effects from Household composition*[b]	
Treatment Variable(MIG_i) [a]			Treatment Variable(MIG_i) [b]	
Any_Parent_Migrated	2.397 (2.82)***		*Any_Parent_Migrated*	1.118 (1.28)
*Any_Parent_Migrated * Poor*	-2.271 (1.79)*		*Any_Parent_Migrated * Nosibling*	0.195 (0.15)
Father_Migrated_Only (mother stayed home)	2.958 (2.83)***		*Father_Migrated_Only (mother stayed home)*	2.028 (1.87)*
*Father_Migrated_Only*Poor*	-1.170 (0.72)		*Father_Migrated_Only*Nosibling*	0.965 (0.57)
Father_Migrated (Unconditional)	2.668 (2.85)***		*Father_Migrated (Unconditional)*	1.516 (1.60)
*Father_Migrated * Poor*	-2.139 (1.54)		*Father_Migrated * Nosibling*	0.028 (0.02)
Mother_Migrated_Only (Father stayed home)	2.285 (1.59)		*Mother_Migrated_Only (Father stayed home)*	-0.828 (0.40)
Mother_Migrated_Only Poor*	-3.783 (1.28)		*Mother_Migrated_Only* Nosibling*	1.680 (0.48)
Mother_Migrated (Unconditional)	1.349 (0.99)		*Mother_Migrated (Unconditional)*	-0.403 (0.29)
*Mother_Migrated * Poor*	-3.369 (1.62)		*Mother_Migrated * Nosibling*	-0.174 (0.08)
Both_Parents_Migrated	1.720 (0.87)		*Both_Parents_Migrated*	0.155 (0.08)
*Both_Parents_Migrated * Poor*	-3.982 (1.38)		*Both_Parents_Migrated* Nosibling*	-1.457 (0.48)
Data source: Authors' survey. Robust t statistics in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%				

[a] The regression model used in Panel A is $\Delta Score_i = \alpha + \delta_1 MIG_i + \delta_2 * MIG_i * poor + \gamma Score\_02_i + \beta Xi + \varepsilon i$, where i is the index for the student, *MIGi* is the treatment variable and it takes six forms (see Table 3 for the definitions of the six forms), poor is the housing value dummy in 2002 which equals to 1 if the housing value was worth more than 5000 in 2002 and 0 otherwise, $Score\_02_i$ is the second term score of student i in 2002 and both δ1 and δ2 are reported in column (1). Covariates X_i are the same as those in Table 2.

[b] The regression model used in Panel B is $\Delta Score_i = \alpha + \delta_1 MIG_i + \delta_2 * MIG_i * Nosibling + \gamma Score\_02_i + \beta X_i + \varepsilon_i$, where *i* is the index for the student, *MIGi* is the treatment variable and it takes six forms (see Table 3 for the definitions of the six forms), *Nosibling* is the sibling dummy in 2002 which equals to 1 if the student had no siblings in 2002 and 0 otherwise, $Score\_02_i$ is the second term score of student i in 2002, and both of δ_1 and δ_2 are reported in column (2). Covariates X_i are the same as those in Table 2 except that we exclude a sibling dummy variable.

Appendix A. Summary Statistics of Control Variables Used in the Multivariate Analysis in Rural China in 2002.

	Control Variables	*Never Migrant*		*Any Parent Migrated*		*Total*	
	Characteristics of the students						
(1)	Gender dummy(=1 if male and 0 if female)	0.56	(0.50)	0.58	(0.50)	0.55	(0.50)
(2)	Age of students when they were in the first grade	7.86	(0.96)	7.92	(0.92)	7.87	(0.96)
(3)	Cadre dummy (=1 if the student was a student cadre and 0 if not)	0.34	(0.47)	0.30	(0.46)	0.33	(0.47)
(4)	Mentor dummy (=1 if the student had a mentor and 0 otherwise)	0.87	(0.34)	0.87	(0.33)	0.86	(0.35)
(5)	Sibling dummy (=1 if the student had no siblings and 0 otherwise)	0.29	(0.46)	0.38	(0.49)	0.33	(0.47)
	Characteristics of the parents						
(6)	Age of the father (Years)	34.74	(4.31)	34.60	(4.30)	34.62	(4.28)
(7)	Education of the father (Years of schooling)	7.80	(2.32)	8.03	(2.73)	7.84	(2.47)
(8)	Education of the mother (Years of schooling)	7.19	(2.66)	7.17	(2.91)	7.15	(2.81)
	Characteristics of the household						
(9)	Size of total household land holding (mu)	6.45	(5.01)	5.77	(5.51)	6.17	(5.26)
(10)	Number of household members (Person)	4.58	(1.14)	4.40	(1.20)	4.53	(1.16)
(11)	House value dummy (=1 if the house value is worth more than 5000 yuan)	0.50	(0.50)	0.56	(0.50)	0.52	(0.50)

Data source: Authors' survey

Notes: Mean values are reported in the table with standard deviation in the parenthesis.

Never Migrant is a household in which both parents stayed at home in both 2002 and 2006.

Any Parent Migrated is a household in which both parents stayed at home in 2002 and at least one parent (either the father; mother or both parents) outmigrated in 2006.

Appendix B

Model Specification for Assessing Effect of Migration on School Performance with Heterogeneous Effects

In analyzing the effect of migration, we examine whether or not the impact is different for the students of different households. To be specific, we examine the heterogeneous effects from wealth and household composition.

To examine the heterogeneous effects, we estimate the following models:

Model (5): $\Delta Score_i = \alpha + \delta_1 MIG_i + \delta_2 * MIG_i * poor + \gamma Score\_02_i + \beta \mathbf{X}_i + \varepsilon_i,$

Model (6): $\Delta Score_i = \alpha + \delta_1 MIG_i + \delta_2 * MIG_i * nosibling + \gamma Score\_02_i + \beta \mathbf{X}_i + \varepsilon_i,$

where i is the index for the student, *MIGi* is the treatment variable and it takes six forms[3], poor is the housing value dummy in 2002 which equals to 1 if the housing value was worth more than 5000 in 2002 and 0 otherwise, *Nosibling* is the sibling dummy in 2002 which equals to 1 if the student had no siblings in 2002 and 0 otherwise, $Score\_02_i$ is the second term score of student i in 2002. δ_2 in all the above Models (5) and (6) is the wealth effect and household composition effect respectively. We present results of δ_1 and δ_2 for the above specifications in table 5.

Endnotes

[1] In the case of the students that were held back, we recorded the grades of the first grade year, which unless the child had only been held back for first grade year, was prior to the 2001/2002 academic year. Although we have not included a control for "held back" in our model in this paper, in an alternative version of the model (not shown for brevity), we included such a variable and there was no effect on our results.
[2] Finally, we also included information in the survey to control for other observed factors that might be expected to affect school performance (that can be used as control variables). Three sets of variables were collected. In a set of questions about the characteristics of each student we collected information about each student's gender, age, the number of times that they were held back by a grade, and asked them whether or not they were student cadres. The survey form also included questions on the characteristics of each student's parents and family. The data set includes variables on each parent's age and education attainment as well as the household's land holdings and the total number of other household members.
[3] Yuan is the Chinese currency. One dollar is about 7.6 yuan.
[4] Since we count the migration activities of the parents of these children as treatments before the period of study, these households are not included in the study.
[5] The term, wealth, when used in the rest of the paper will refer to the value of housing assets only.
[6] Other studies in China have found that there is no significant effect of household composition on grades.
[7] In fact, the migrant households can be any one of the six types of migrant households or treatment groups.
[8] We need to note, however, that a recent study found that the propensity score matching method is sensitive to the covariates used to estimate the scores and that combination of matching with DD was superior (Smith and Todd 2004). We account for this comment below.
[9] The results are available upon request.
[10] Using outcomes from experimental data as a benchmark, Smith and Todd (2004) found that DDM performed better than DD or PSM methods.
[11] In another paper, they show that boostrapping is inappropriate for estimating standard errors for matching methods with a fixed number of matches (Abadie and Imbens, 2005).
[12] This is accomplished by assigning an arbitrarily high weight to the exact matching variable in defining the matching criteria.
[13] For completeness in Table 3, we include the results of the effect of Any Parent Migrated on school performance, but, in fact, this is a duplication of the results from Table 2, row 1.
[14] It is important to note that according to theory, PSM and DDM are designed to account for at least part of the unobserved heterogeneity that might be causing any selection bias, so, in fact, it can be argued that we have addressed this concern. Moreover, although we raise this issue because it theoretically is possible, in fact, in practice there is reason to believe it is not that serious of a statistical problem. We believe this because this is only a problem parents will only choose NOT to migrate if the cost of lower grades is higher than the benefits of migrations. We do not believe this is true, in general. The cost of lower grades FOR PARENTS is going to show only in the future—in our case 5 to 10 years later when these children enter the job market. The benefits of migration, on the other hand, accrue to the family immediately. Taking into account that the discount rate for individuals in developing countries is generally quite high, it is reasonable to say that lower grades will not stop most parents from migrating.