# Working Paper Series 641 (ISSN 1211-3298)

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CERGE-EI Prague, April 2019

ISBN 978-80-7343-448-9 (Univerzita Karlova, Centrum pro ekonomický výzkum a doktorské studium) ISBN 978-80-7344-501-0 (Národohospodářský ústav AV ČR, v. v. i.)

# Seasonal Migration and Education of Children Left Behind: Evidence from Armenia<sup>§</sup>

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April 15, 2019

#### Abstract

There is much evidence that migration of a parent affects the educational performance of children left behind (CLB). Nevertheless, there is no agreement on the direction of the impact. In this paper, we use Armenian school data and report evidence of a negative impact of parental seasonal migration on the educational performance of CLB. We employ a different approach than those used in the prior literature by (i) using the intensity of seasonal migration (the number of times the parent migrated) instead of a binary variable (whether the parent migrated or not) and (ii) the number of children entering first grade whose parent is a seasonal migration negatively affects the educational performance of CLB, and that it mainly affects boys; there is no significant impact on girls. Additionally, we find that using a zero-one dummy for migration as prior studies have done upwardly biases the IV estimate by approximately a factor of three, while our intensity measure yields more accurate results.

*JEL Codes: F22, I26, J13, O15 Keywords:* seasonal migration, children left behind, educational performance

<sup>&</sup>lt;sup>§</sup>This study was supported by Charles University, GAUK project No. 88218. We thank Nikolas Mittag, Stepan Jurajda, Mariola Pytlikova, Randall Filer, Deborah Novakova, Bohdana Kurylo and Jaroslav Groero for their useful comments and suggestions and Karine Harutunyan from National Institute of Education in Armenia for her help with the data collection. Any remaining errors are our own. The views expressed here are those of the authors and not necessarily those of CERGE-EI.

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#### Introduction

A significant share of the labor force in many developing countries is engaged in seasonal migration, so the impacts of seasonal migration on the next generation are potentially important. In particular, the potential impact of a parent's seasonal migration on the educational performance of children left behind (CLB) has triggered considerable attention from policymakers and researchers. However, previous studies find mixed evidence. Some papers (e.g. McKenzie & Rapoport, 2011; Davis & Brazil, 2016; Antman, 2011) find that seasonal migration negatively influences the educational performance of CLB, while other studies (Theoharides, 2018; Bai et al., 2018) find a positive effect. Possible reasons for the mixed evidence may be differences between countries where the studies are conducted<sup>1</sup>, identification strategies, and alternative measures of child performance used by researchers.

Identification of the causal effects of seasonal migration on the educational performance of CLB is complicated by two main issues. First, seasonal migration decisions of parents are potentially endogenous with respect to the performance of their children. To overcome this issue, most existing studies use instrument variables (IVs), such as historical migration networks (McKenzie & Rapoport, 2011; Davis & Brazil, 2016), the age of the head of the household (Bucheli, Bohara, & Fontenla, 2018), a sibling's age at the time of parental migration (Antman, 2012), and demand shocks in destination countries (Antman, 2011; Cortes, 2015; Theoharides, 2018). The advantages and disadvantages of these instruments are extensively discussed in the literature, for

<sup>&</sup>lt;sup>1</sup> In some origin countries, the positive effect of remittances may dominate the possible negative effects associated with the temporary loss of one parent, while in other countries remittances might have a second-order effect.

instance, see Antman (2012) for an excellent review. The second issue, which does not receive much attention in the migration literature, is that the educational performance of CLB is likely affected by the intensity of seasonal migration (the number of times a parent has migrated) rather than by seasonal migration in general (whether or not a parent has ever migrated). In general, coarsening of the main treatment effect (seasonal migration) into a zero-one dummy variable results in a drastically overestimated coefficient, when a valid instrument is used to identify the causal effect (Angrist & Imbens, 1995). The intuition is that the estimated coefficient shows the sum of the effects from migrating and an increase in the intensity of migration, which was due to the specific instrument used by the researcher.

The only way in which coarsening of the seasonal migration does not lead to biased estimates is when the instrument used by the researcher influences the extensive margin (the parents switching from stayers to movers), but not the intensive margin (duration or times of migration) of seasonal migration. Instruments used in previous studies are not likely to satisfy this criterion. For example, the age of the head of the household affects the intensity of seasonal migration, as younger individuals may have higher returns to migration. Region-specific historical migration rates may also affect the average duration of seasonal migration, as larger social networks might make it easier to stay longer in the host country. Finally, demand shocks in destination countries may discourage seasonal migrants from returning or staying longer and, hence, also affect the intensity of treatment beyond moving people in and out of seasonal migration.

Using administrative student-level data from Armenian school districts on first graders entering the school system and on students in their last year of school, this paper identifies the overall impact of the intensity of seasonal migration by a parent on the educational performance of CLB and contributes to the existing literature in the following ways. First, our analysis finds that using a zero-one dummy for migration as prior studies have done upwardly biases the IV estimate by approximately a factor of three. Second, in contrast to previous studies that use the number of schooling years or the probability of completing high school<sup>2</sup> as a measure of the educational attainment of CLB, we use students' math test scores<sup>3</sup> in their last year in school. This allows us to explore the possible effects of parental seasonal migration on the intensive margin of educational performance. Furthermore, in countries with mandatory secondary education, the high school dropout rate does not reflect the educational investment of children and their parents when the dropout rate is very low.

We use the number of children entering first grade whose parent is a seasonal migrant as an instrument for the intensity of seasonal migration. The main identification assumptions behind our instrument are as follows. First, the number of children entering first grade whose parent is a seasonal migrant does not affect the educational performance of children other than through the seasonal migration decision of their parent. This means that parents do not strategically sort their children into first grade with respect to seasonal migration and that there are no peer effects between CLB and other children. We control for school fixed effects and exclude schools that are close to the capital of Armenia, where families may have a choice of schools. This helps us to decrease the probability of

<sup>&</sup>lt;sup>2</sup> Antman (2011), Antman (2012), McKenzie and Rapoport (2011), Theoharides (2018), Cortes (2015) <sup>3</sup> To the best of our knowledge, Bai et al. (2018) is the only paper to study the effects of international parental migration on test scores.

strategic sorting into schools, and to control for school quality, which is a major issue if one uses historical migration rates as an instrument for selection into seasonal migration (Antman, 2012).

Second, we test for the absence of peer effects between CLB students and others by regressing the math test scores of students in their last year in school<sup>4</sup> from nonmigrant families and the test scores of students whose parents have migrated at least once (excluding those children in the first grade whose parents were seasonal migrants) on our instrument. We do not find any direct effect of our instrument on the educational performance of students who are not CLB, and find a negative effect on the performance of students whose parents migrated at least once. The absence of an effect on non-CLB students is consistent with the absence of a peer effect. The negative "reduced form" impact on children of migrating parents is in line with our identification strategy.

Our findings suggest that seasonal migration of a parent negatively affects the educational performance of CLB. This negative effect is mainly driven by a decrease in the educational performance of boys; the effect on girls is small and not statistically significant. The results of our study are in line with the findings of McKenzie and Rapoport (2011), who suggest that there may be a negative incentive effect if the returns to education for seasonal migrants in the destination country are lower than in their home country. Another possible reason may be that CLB boys increase their time spent doing housework to substitute for the labor shortage associated with paternal migration, which in turn may decrease their educational performance. Male role model effects are another

<sup>&</sup>lt;sup>4</sup> This means the last year that we observe, which depending on the cohort it can be from 6<sup>th</sup> to 12<sup>th</sup> grade.

possible channel, as in the majority of cases the Armenian father is the seasonal migrant, hence, CLB boys may perform worse due to temporary loss of their male role model. To explain which of these channels is responsible for the heterogeneity of seasonal migration effect with respect to gender, deeper analyses are required, with possible use of shocks to returns to education that affect only the incentive channel.

The remainder of this paper is organized as follows. Section 2 discusses the related literature. Section 3 describes the data used for the empirical analysis and contrasts it with other datasets that are used in the literature. Section 4 discusses our identification strategy. The results on the impact on the educational performance of CLB are presented in Section 5 and Section 6 concludes.

#### 2. Literature Review

The migration decision of a family member may affect the quality of life of household members left behind through a variety of channels. In the context of education of CLB, there are two main channels distinguished in the literature, representing negative and positive impacts. On the positive side, seasonal migrants tend to support their families by sending remittances, which can give children more education opportunities in their home countries (Acosta, 2011; Edwards & Ureta, 2003; Yang, 2008). Conversely, recent literature on the "beneficial brain drain" suggests that if education has lower/higher returns when migrating, the prospect of migrating in the future decreases/increases the expected returns to education, inducing children to invest less/more in domestic education (Commander, Kangasniemi, & Winters, 2004; Beine et al., 2007; McKenzie & Rapoport, 2011). Furthermore, the absence of a parent from the house can decrease the time parent

devotes to a child, which may worsen educational performance. According to Antman (2011), children decrease study time and spend more hours doing housework, working in the labor force when fathers are away. Therefore, depending on which of these channels are activated, the overall effect of a parent's migration can differ in sign.

It is widely accepted in the literature that the factors that affect a parent's migration decision affect also a child's educational performance. In other words, there is an endogeneity issue. In order to solve it, most papers in the field that use observational data use different instrumental variables<sup>5</sup>. McKenzie and Rapoport (2011)<sup>6</sup> choose historical rates of migration by states as an instrumental variable, assuming that it affects the decision to migrate, but not the education of CLB. They find that parental migration negatively affects the school attendance of 12 to 18-year-old boys and 16 to 18-year-old girls. This is in line with the findings of Davis and Brazil (2016), who use historic community migration networks as an instrument for the seasonal migration decision, and the US receiving community wages (measured as average wage for low skilled workers in 25 large US cities) as an instrument for remittances. They conclude that the absence of a parent has a negative impact on school enrollment. For those students who remain in school, remittances can neutralize the negative influence of fathers' absences on educational performance. However, as highlighted by Antman (2012), historical migration rates might not satisfy the main conditions of an instrumental variable. More precisely, historical migration rates may affect educational attainment of CLB, because they may be an indicator of the prevalence and quality of schools in the area.

<sup>&</sup>lt;sup>5</sup> Though some studies rely on matching and fixed effects (Kuhn et al., 2011; Antman, 2011c).

<sup>&</sup>lt;sup>6</sup> Hanson and Woodruff (2003); McKenzie and Rapoport (2011) also use historical migration rates.

The second common instrument used in the literature is the demand shocks in immigrant-receiving countries. Theoharides (2018) analyzes the effect of international migration on children's secondary school enrollment in their country of origin by exploiting destination-country labor demand shocks for seasonal migrants (a similar identification strategy is used by Cortes, 2015). In a destination-country province-level analysis, Theoharides (2018) finds that secondary school enrollment in total increases by 3.5 % as a response to an average year-to-year increase in migration demand. Some studies compare the impact of seasonal migration on the children of migrant mothers versus the children of migrant fathers. Cortes (2015) studies how the migration of mothers affects the school performance of Filipino CLB. She finds that the children of migrant mothers are significantly more likely to lag behind in school than the children of migrant fathers. However, compared to non-migrant families, children benefit from their mother's decision to migrate. Sarma and Parinduri (2016) do similar analyses using access to foreign employment agencies as a source of exogenous variation. They find that the impact on children's education is negative when the mother migrates, and the father stays, and positive in the opposite case. Nevertheless, these two cancel each other out and, overall, there is no impact.

Another instrument used in the literature of seasonal migration is the age of the head of the household (Bucheli, Bohara, & Fontenla, 2018). The main idea behind this approach is that the age of the head of the household is potentially exogenous to socioeconomic conditions in the origin country and does not affect schooling decisions, but affects the probability of migrating and sending remittances. Bucheli, Bohara, and Fontenla (2018) use an indicator of whether an individual is between 20-50 years old and indicators of economic conditions in primary destinations as instruments for sending remittances. They find that the effect of remittances is positive for boys and negative or insignificant for girls in Ecuador.

However, the age of the head of the household might also affect the schooling decisions of children through other channels. For example, the age of the head of the household is correlated with the age of the children which may, in turn, influence the schooling decisions of children. Thus, the main exclusion restriction is not likely to hold. In contrast, we use the number of parents who are seasonal migrants with children starting the first grade as an instrument for the future seasonal migration decision of the household. The underlying identification assumption is that the initial number of households with a parent who is seasonal migrants when a child starts first grade increases the probability of seasonal migration by parents of other households by providing information about the returns to migration and reducing the associated uncertainty. Section 4 discusses possible threats that could potentially invalidate the instrument and result in biased estimates.

Another potential identification issue, which does not receive much attention in the migration literature, is that the seasonal migration indicator is a coarsened proxy of the underlying years in seasonal migration (or seasonal migration intensity) variable. As shown by Angrist and Imbens (1995), incorrectly parametrizing seasonal migration into an indicator variable results in drastically overestimated coefficients, even when one uses a valid instrument to identify the causal effect. Similar reasoning applies when one uses a remittances indicator (whether a family receives remittances or not) instead of the amount of the remittances received (Bucheli, Bohara, & Fontenla, 2018). Marshal (2018) analyses the effect of high school education on voting behavior and shows that coarsening years of schooling into an indicator variable upwardly biases the IV estimate by a factor of three. As our data contains information about the number of years a parent spent in migration, we are able to identify the causal effect of seasonal migration intensity on the educational performance of CLB which does not suffer from the upward bias discussed above.

This study contributes to the literature on the impact of seasonal migration in two ways. To our knowledge, this is the first study examining the effect of the intensity of seasonal migration on the educational performance of CLB. Our analyses reveal that incorrect coarsening of seasonal migration into a zero-one dummy variable upwardly biases the IV estimate approximately by a factor of three. Second, in contrast to previous studies that use the number of years of schooling or the highest degree attained as a measure of educational attainment of CLB, we use student math test scores. This allows us to explore the possible effect of seasonal migration on the intensive margin of educational performance. This feature is particularly important for developing countries, where a school dropout is a rare phenomenon.

#### 3. Data Description

Seasonal migration to Russia is a primary means of financial support for a considerable number of Armenian families, especially in regions outside Yerevan. According to a labor statistics survey conducted by the Russian-Armenian University, in 2013, around 21 percent of the male labor force of Armenia worked abroad. The main

destination of these labor migrants is Russia (96%<sup>7</sup>), which can be explained by Armenian's basic knowledge of the language (Russian is taught as a foreign language in Armenian schools) and comparably higher salaries. Because of the types of the jobs these migrants mainly do (e.g. working in construction) the overwhelming majority (93.5%) of Armenian labor migrants are men aged 21-50 and, 76% are married. Again, mainly because of the type of the jobs they migrate for, most seasonal migrants leave Armenia in spring and return by the end of autumn/beginning of winter. In other words, the migration is seasonal and, on average, lasts about 9 months. Migrant workers are generally informed about job opportunities by their friends and relatives living in the host country (42%), or by their social connections at home (15%). These general conditions demonstrate that Armenia is a useful example for study of the effects of seasonal migration, especially in the context of children left behind, considering that most Armenian seasonal migrants have families.

Our data is from school records compiled by teachers, which contain information on the age, gender and math test scores (our main outcome variable) of students for each semester, the employment status of the head of the household (coded as high, middle, low and self-employed), the seasonal migration history of their father and the size of their class. The pilot version of the administrative individual-level data is being collected by Karine Harutunyan of the National Institute of Education in Armenia<sup>8</sup>, with the permission of the Ministry of Education of Armenia. It is still in process, and the goal is to cover 100 randomly selected schools across Armenia. For this study, we use data which

<sup>&</sup>lt;sup>7</sup> Assessment of RA migration situation through sample survey: <u>http://www.rau.am/uploads/blocks/3/31/3115/files/Migration\_Project\_Report\_final.pdf</u>

<sup>&</sup>lt;sup>8</sup> The collection of the data was supported by Charles University, GAUK project No. 88218.

has already been collected, and includes 30 schools from Yerevan, the capital city, and the Armavir regions.

The data includes 20 high schools (from 10<sup>th</sup> to 12<sup>th</sup> grade) in Yerevan<sup>9</sup> and 10 schools (with classes from first to 12<sup>th</sup> grade) in the rural Armavir region. Education is mandatory in Armenia till 9<sup>th</sup> grade, and 98% of students continue studies after the 9<sup>th</sup> grade<sup>10</sup>. The data is collected in the following way. From each observed school in Yerevan, one class from each of three cohorts (2007, 2010, and 2012) is randomly chosen. All students are followed through 12<sup>th</sup> grade (that is for 3 years), conditional on their staying in that school. From the rural Armavir region, 10 secondary schools are randomly chosen, and classes are randomly chosen within the schools. All students in Armavir schools are observed from first grade through 12<sup>th</sup> grade (in six cohorts from 2007 to 2012 to 2017), conditional on their staying in that school. Therefore, the pilot version of the data is representative for Armavir (rural region) and Yerevan (capital city). It contains information on 3,223 households from 2001 to 2017.

We need to follow students from the first grade because we use the number of children entering first grade whose parent is a seasonal migrant as an instrument. For this we exclude observations from Yerevan. Furthermore, in order to solve the issue of strategic sorting into schools, we use data from regional schools that are more than ten kilometers away from Yerevan, and exclude data from schools in large regional cities. The households in rural areas do not have a wide choice of schools and, therefore, are not likely to sort into schools, but will enroll in the one nearby. In fact, in our restricted sample

<sup>&</sup>lt;sup>9</sup> There are 35 high schools in total in Yerevan.

<sup>&</sup>lt;sup>10</sup> Source: Armenia - Education Policy Data Center.

there are only two districts with two schools; the rest have only one school available in the district<sup>11</sup>. We also exclude data on students who left the school (the majority moved to Russia with their family, 48 individuals) and keep only students we can follow till 2017 – for at least 6 years. Under these restrictions, our final sample includes 6 cohorts (from 2007 to 2012) from 9 random schools with 1,017 households.

VARIABLES	Mean	Min	Max	Std. Dev
Math test score	6.51	3	9	1.56
Male	0.51	0	1	0.5
Migration (Binary)	0.42	0	1	0.49
Migration (Intensity)	1.61	0	10	2.4
Class size	21.89	16	33	3.85
Observations	1017			
Migration (Intensity) conditional on going at least once	3.87	1	10	2.27
<b>Observations</b>	423			

Table 1. Summary statistics of main variables

From the summary statistics of the main variables (Table 1), it is clear that the sample is gender balanced – around 51% are boys. Our dependent variable, the average math test scores, is 6.51 on a scale of 9, and the standard deviation between the scores is quite large (1.56). Around 42% of the students' fathers went for seasonal migration at least once. In addition to this, the intensity variable shows how many times a father went for seasonal migration, from zero to 10 times. We should highlight that, even though more than half of the fathers were never on seasonal migration (in other words, even with around 58% of zeros in the sample) the average intensity is 1.61. This leads us to the idea

<sup>&</sup>lt;sup>11</sup> This is mainly because the data was designed to be representative of the rural Armavir region rather than the whole country.

that if, a father went on seasonal migration once, then most probably he will repeat it. The histogram of intensity conditional on going for seasonal migration at least once shows this to be the case (Figure 1). With this condition, the mean of intensity increases to almost 4 (Table 1), which means that, conditional on going for seasonal migration at least once, fathers repeat the migration on average 4 times. Only 14% of our seasonal migration instead of a simple zero-one dummy for migration, because the latter can lead to overestimated coefficients.

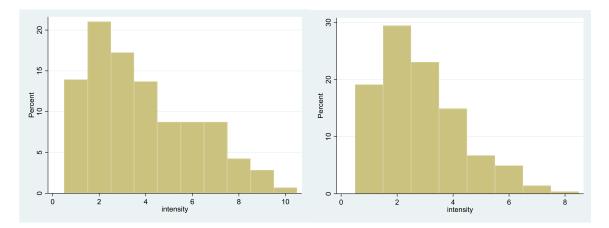


Figure 1. The histogram of seasonal migration intensity: conditional on going for seasonal migration at least once (on the left) and for treated individuals excluding those who were seasonal migrants when their children started first grade (on the right).

Our data has two distinctive features compared to other datasets used in the literature. First, we have a well-measured outcome variable (math test scores), which allows us to explore the possible effect of seasonal migration on the intensive margin of educational performance. The other measures used in previous literature (e.g. the number of schooling years, or probability of dropping out of school) are not applicable in many developing countries where the dropout rate is very small (e.g. Ukraine, Georgia,

Armenia). Second, in contrast to other datasets that provide information only about whether a person has ever migrated seasonally for work (or migrated within the last 5 years), we observe the intensity of seasonal migration (number of times a parent goes for seasonal migration). This information is crucial to consistently estimate the effect of seasonal migration on the educational performance of CLB. In the next sections, we show that with a simple zero-one dummy for migration, the impact of seasonal migration is highly overestimated.

#### 4. Empirical Methodology and Identification Strategy

Identification of the causal relation between seasonal migration and the educational performance of CLB is complicated for two main reasons. Firstly, the seasonal migration decision is endogenous, and comparing the outcome of families with seasonal migrants to those without will generally give biased estimates. The second issue, which does not receive much attention in the migration literature, is that the educational performance of CLB is affected not only by seasonal migration (whether a parent has ever migrated) but also by the intensity of seasonal migration (the number of times a parent has migrated). Incorrect parameterization of seasonal migration into an indicator variable results in a drastically overestimated coefficient even when one uses a valid instrument to identify the causal effect (Angrist and Imbens, 1995). Sections 4.1 and 4.2 discuss these two issues and present our solutions.

#### 4.1 Endogeneity of the Seasonal Migration Decision

To estimate the overall effect of seasonal migration, one needs to control for the endogeneity of the seasonal migration decision. Some studies (Bucheli, Bohara, & Fontenla, 2018) use the age category of the head of the household as an instrument for the seasonal migration decision. The idea behind this approach is that the age of the household head is correlated with the decision (and sending remittances), and those studies assume that parental age does not directly affect the educational attainment of children. However, the age of the household head may directly affect the educational attainment of siblings.

Alternatively, McKenzie and Rapoport (2011) and Davis and Brazil (2016) use state (region)-level historical migration rates as an instrument. The idea behind this approach is that historical migration stocks reduce the price of migration for current migrants, and if the time period between the past migration and the observation period is large enough, historical migration will not affect the education of children directly. Though the method has clear advantages over other methods used in the literature, it is not appropriate for studies of many developing countries due to the absence of historical migration data or to small numbers of regions. Furthermore, historical migration rates may affect current educational performance of children via brain drain and the resulting intergenerational transition of educational skills, as well as through changes in infrastructure and school quality.

Our data does not contain information on district level historical migration flows, instead, we use the number of parents who are seasonal migrants when their children start

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first grade as an IV for future seasonal migration decisions. The underlying identification assumption is that the initial number of households with parents who are seasonal migrants when their children start first grade increases the probability of seasonal migration of other parents through information provision and reduction in the costs of migration. For our instrument to be valid, it should not affect the educational performance of children other than through the seasonal migration decisions of their parents. As the validity of the instrument is crucial for our analyses, we next discuss possible threats that could potentially invalidate the instrument and result in biased estimates.

The first challenge is that our instrument may affect the performance of children through their peers and consequently change the incentives of non-CLB students to study. To test for the validity of our instrument, we regress math test scores of children whose parents have never migrated on our instrument. We also regress math test scores of children whose parents have migrated at least once (excluding those children whose parents were seasonal migrants when they started the first grade) on our instrument. We do not find any direct effect of our instrument on the educational performance of non CLB students, and find a negative effect on the educational performance of children whose parents have migrated at least once, which is a piece of suggestive evidence in favor of the validity of our instrument (Appendix A, Table A4, Columns A and B respectively).

Another potential threat is possible positive sorting into higher-quality schools, or that households may strategically choose schools. If this is the case, then the differences in the initial number of households with seasonal migrant parents may not be random, because families with parents who are not likely to become seasonal migrants may cluster

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into different schools, which in turn will invalidate our results. We propose two strategies to overcome this issue. First, we control for school fixed effects. Second, we use data from regional schools that are more than ten kilometers away from Yerevan and exclude schools in large regional cities and in Yerevan. We believe that this will solve the issue, as households in rural areas do not have a large choice of schools (in fact in our restricted sample there are only two districts with two schools, the rest have only one) and, therefore, households are not likely to sort their children into schools but rather to attend the nearby schools.

#### 4.2 Coarsening the Treatment Effect

The second issue is that the educational performance of CLB is likely to be affected not by parental seasonal migration (whether one of parents has ever migrated) but rather by the intensity of seasonal migration (the number of times a parent has migrated). Incorrectly parametrizing seasonal migration into an indicator variable results in a drastically overestimated coefficient even when one uses a valid instrument to identify the causal effect (Angrist & Imbens, 1995). Formally, let  $y_i$  for  $i = \{1; ..., N\}$  be the outcome of interest (for example, the number of schooling years completed by student *i*, or math test scores) and let  $S = \{0; 1; ..., J\}$  indicate the seasonal migration intensity and assume that it is the true treatment variable. Nevertheless, because of data limitations, the researcher parametrizes S as a binary variable  $M = \{0; 1\}$  that equals one if S > 0 and 0 otherwise. Assume, further, that the researcher has a valid instrument Z, which we will assume to be binary for simplicity. The instrumental variable estimation of the effect of binary seasonal migration may be expressed in the following way.

Outcome equation (excluding other covariates for simplicity) is:

$$y_i = \alpha + M_i \beta + \varepsilon \tag{1}$$

The first stage equation is:

$$M_i = \alpha_1 + Z_c \delta_1 + \eta_1 \quad (2)$$

Where equation (1) is the outcome equation (we exclude other covariates for simplicity) and equation (2) is the first stage regression of our endogenous variable (seasonal migration indicator) and instrument. Then, following Angrist and Imbens (1995), the IV estimate of the treatment effect is given by:

$$\beta^{IV} = \frac{E[S|Z=1] - E[S|Z=0]}{E[M|Z=1] - E[M|Z=0]} \beta = \frac{\sum_{j=1}^{J} \Pr(S_1 \ge j > S_0)}{\Pr(S_1 \ge 1 > S_0)} \beta = \varphi\beta$$
Where  $\varphi = \frac{\sum_{j=0}^{J} \Pr(S_1 \ge j > S_0)}{\Pr(S_1 \ge 1 > S_0)}$ 

Note that the only situation where  $\varphi = 1$  is when the instrument has no effect other than to cause people to switch from S = 0 to S = 1. In all other cases E[S| Z = 1] – E[S| Z = 0] > E[M| Z = 1] – E[M| Z = 0]. Therefore, when a treatment variable is incorrectly parameterized as binary, the resulting estimate tends to be too large relative to the average per unit effect along the length of the response function<sup>12</sup>. The instruments used by previous studies are not likely to satisfy this criterion. For example, the age of the household head affects the intensity of seasonal migration, as younger individuals might have higher returns to migration than older individuals

<sup>&</sup>lt;sup>12</sup> Angrist and Imbens (1995).

The region-specific historical migration rates may also affect the average duration of seasonal migration, as larger social networks might decrease the cost of a stay in the destination country. For example, individuals from regions with higher historical migration rates may be more prone to stay in migration longer as the cost of staying abroad is presumably smaller for them. Finally, the demand shocks in destination countries might discourage former seasonal migrants from staying longer in migration spells, affecting the intensity of treatment beyond moving people in and out of the seasonal migration.

The instrument that we use in this study is also likely to affect the intensity of seasonal migration, because the number of households with seasonal migrant parents when children start first grade is likely to increase the seasonal migration intensity. Therefore, unlike other studies, we observe how many times a parent has gone for migration during the years his/her child is in school. This allows us to overcome the issue of incorrectly coarsening the treatment effect discussed above and to assess the magnitude of the bias associated with incorrect parameterization of seasonal migration into a binary variable.

As seasonal migration intensity takes on values from  $\{0; 1; ...J\}$  one needs to estimate J casual effects i.e. the effect of changing from 0 to 1, from 1 to 2 and so on. This is problematic in practice because one would need multiple instruments that shift the seasonal migration intensity from  $S_{j-1}$  to  $S_j$  for  $j = \{1, ...J\}$  but not from  $S_{l-1}$  to  $S_l$  for  $l \neq j$ . Instead we use a linear causal model and assume that the treatment effect is the same for all S. This assumption is obviously unrealistic, however, as pointed out by Angrist and Pischke (2008), 2SLS provides a weighted average of unit causal effects.

Furthermore, different instruments will provide different results because they act at different levels of the distribution of the seasonal migration intensity. Therefore, the positive bias associated with incorrect parameterization of seasonal migration intensity as a binary variable is not necessarily the same if one uses historical migration rates as an instrument versus the number of parents who are seasonal migrants when their children start the first grade.

#### 5. Estimation Techniques and Results

This section identifies the impact of the intensity of parental seasonal migration on the educational performance of CLB. We measure our variable of interest as the math test scores (deviation from the mean) in the second semester of 2017, and perform a 2SLS estimation. As seasonal migration intensity is a count variable that takes values from 0 to 10, the linear first stage might not be appropriate. Therefore, as a robustness check, we specify both linear and non-linear (Poisson) regression for the first stage.

As can be seen in the results in Table 2, columns A and B, the difference in specification does not affect either the size or the significance of the coefficient of our main variable of interest. An increase in seasonal migration intensity by one unit (year) decreases the performance of CLB on average by 0.24 deviation (significant at 5%). With non-linear first-stage regression, neither the sign nor the magnitude of the coefficient of interest change (0.22), and are significant at 5% (Table 2, Column B). These results are in line with previous studies<sup>13</sup> that also find a negative effect of seasonal migration on CLB. The size of a class and the status of parental employment also have coefficients

<sup>&</sup>lt;sup>13</sup> McKenzie and Rapoport (2011); Davis and Brazil (2016); Antman (2011) among others.

with expected signs. Additionally, boys on average perform worse than girls. In all the regressions, standard errors are clustered at school-cohort level and we control for school fixed effects<sup>14</sup>.

	А	В	С	D
VARIABLES	2SLS	2SLS	2SLS	2SLS
	linear	Poisson	Linear	Probit
Migration (Intensity)	-0.248**	-0.217**		
	(0.1147)	(0.1011)		
Migration (Binary)			-0.705**	-0.669**
			(0.3005)	(0.2975)
Male	-0.454***	-0.454***	-0.484***	-0.483***
	(0.0594)	(0.0582)	(0.0627)	(0.0622)
Class size	-0.023*	-0.020	-0.0137	-0.013
	(0.013)	(0.0126)	(0.0109)	(0.0109)
Parent holds				
high skilled job	1.136***	1.139***	1.156***	1.156***
	(0.0715)	(0.0696)	(0.0688)	(0.0681)
School FE	YES	YES	YES	YES
R-squared	0.219	0.245	0.246	0.254
Observations	882	882	882	882

Table 2: The effect of seasonal	migration on the	educational	performance of CLB
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Robust standard errors in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

For comparison we next use a zero-one seasonal migration dummy instead of intensity and repeat our analyses. Here we also use linear and non-linear (Probit) first stage specifications (Table 2, columns C and D, respectively). The sign of the coefficient of the zero-one dummy is the same as the sign for seasonal migration intensity, and it is significant in both linear and non-linear specifications. This is not surprising, because

<sup>&</sup>lt;sup>14</sup> We additionally run the same regressions with cohort fixed effects instead of school fixed effects. The results do not change.

coarsening the treatment effect does not affect the sign but rather the magnitude of the impact. As we can see, the magnitude of the impact is around 3 times larger when we use a simple zero-one seasonal migration dummy instead of seasonal migration intensity.

We also separately repeat the same analyses by gender and find that the impact of seasonal parental migration is stronger for boys. For girls, the coefficient of seasonal migration intensity is close to zero and is non-significant (Table A1, Appendix A). One possible reason for this may be that most Armenian seasonal migrants work in sectors with low educational requirements in Russia (the main destination of seasonal migration). Therefore, boys who see themselves as future seasonal migrants, following in the path of their migrant-worker fathers, have lower educational performance at schools because their expected returns to education are lower. If this logic is true, the negative incentive should not work for girls, because they are less likely to engage in future seasonal migration).

This result is in line with the findings of McKenzie and Rapoport (2011). They suggest that seasonal migration can result in negative incentives if the returns to education for seasonal migrants in the destination country are lower than in the home country. Of course, there may be other stories that explain our results. For example, boys left behind may increase their energy spent on housework to substitute for the household labor shortage associated with paternal migration, which in turn may decrease their educational performance. There may also be role model effects. Identifying the responsible channels for this heterogeneity of seasonal migration effect with respect to gender is beyond the scope of this study.

#### 6. Conclusion

We analyze the effect of parental seasonal migration on the educational performance of children left behind (CLB). Using individual level data from Armenia, where we can follow the same children and their families for at least 6 years, we show that incorrect specification of seasonal migration into a binary variable leads to a significant upward bias. Furthermore, it biases the main estimate approximately by a factor of three. To our knowledge, we are the first to highlight this issue in the context of migration and to correct for it.

In order to avoid the endogeneity issue, we propose a new instrumental variable, which has some advantages compared to those used previously. Of course, the share of parents who are seasonal migrants at the start of the school year, which we use as an IV, also has some disadvantages. Nevertheless, we perform additional robustness checks and claim that these disadvantages should not affect our main results. Additionally, instead of using educational attainment (e.g. years of schooling – extensive margin) of children as a variable of interest, we use their math test scores, which allows us to analyze the impact of seasonal migration on the intensive margin of educational performance. The latter is a preferable measure for developing countries like Armenia, where dropping out of school is a rare phenomenon.

We find that the overall effect of seasonal migration on the educational performance of CLB is negative. Furthermore, this negative effect operates mainly through a decrease in the performance of boys left behind. The seasonal migration of parents (mainly fathers) has no significant impact on the educational performance of girls. The latter leads us to the idea that the educational performance of boys may decrease because of the negative incentive of their own future seasonal migration prospects, absence of the role model, or increases in housework performed by boys.

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## Appendix A

	А	В
	Male	Female
VARIABLES	2SLS	2SLS
	Poisson	Poisson
Migration (Intensity)	-0.418***	0.047
-	(0.1293)	(0.1295)
Class size	-0.032	-0.003
	(0.0215)	(0.0126)
Parent holds		
high skilled job	1.078***	0.898***
	(0.1431)	(0.0959)
School FE	YES	YES
R-squared	0.153	0.203
Observations	434	448
1 1 1 .	.1 stastasta	0.01

Robust standard errors in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

VARIABLES	Α	В	
	Migration (dummy)	<b>Migration</b> (intensity)	
	(Probit)	(Poisson)	
Number of migrants in the	0.032***	.032***	
first grade (IV)	(0.0039)	(0.0055)	
Parent holds			
high skilled job	0.035	-0.123	
0	(0.1250)	(0.1465)	
Class size	-0.025**	-0.092***	
	(0.0127)	(0.0196)	
Male	-0.1105	0.015	
	(0.0888)	(0.0383)	
School FE	YES	YES	
Pseudo R-squared/ Log pseudo-likelihood	0.0386	-1342.3194	
Observations	882	882	

### Table A2: The first stage regression

VARIABLES	Α	В	
	Migration(intensity)	Migration(intensity)	
	(Poisson) (Male)	(Poisson) (Female)	
Number of migrants in	0.036***	0.027***	
the first grade (IV)	(0.0075)	(0.0055)	
Parent holds	-2.657***	0.433***	
high skilled job	(0.6979)	(0.1325)	
ingii skinea joo	(0.0979)	(0.1323)	
Class size	- 0.077**	- 0.097***	
	(0.0264)	(0.0265)	
School FE	YES	YES	
Log pseudo-likelihood	-629.83968	-1342.3194	
Observations	434	882	

### Table A3: The first stage regression by gender

Robust standard errors in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

	A	В
VARIABLES	Performance of non-migrant children	Performance of children whose parents migrated at least once
IV	-0.0015	-0.0103*
	(0.0051)	(0.0053)
Male	-0.285***	-0.865***
	(0.0707)	(0.105)
Class size	-0.0013	-0.0169
	(0.0102)	(0.0219)
Parent holds	1.099***	1.043***
high skilled job	(0.879)	(0.106)
School FE	YES	YES
R-squared	0.2533	0.4732
Observations	600	282

### Table A4: Check for the validity of the instrument

Robust standard errors in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

We do not find any direct effect of our instrument on the educational performance of non CLB children, which is a piece of suggestive evidence in favor of the validity of our instrument.

#### Abstrakt

Existuje mnoho důkazů, že migrace rodičů ovlivňuje vzdělání dětí ponechaných v místě původu (zkráceně CLB z anglického výrazu childern left behind). Nicméně nepanuje shoda, zda migrace působí negativně nebo pozitivně. V tomto článku využíváme arménská školní data a zjišťujeme negativní dopad sezónní migrace rodičů na výsledky vzdělávání CLB. Využíváme postupy, které se liší od postupů v existující literatuře. Konkrétně využíváme (i) intenzitu sezónní migrace (počet migrací rodičů) místo binární proměnné (zda rodič migroval nebo ne) a (ii) počet dětí nastupujících do první třídy, jejichž rodiče jsou sezónními migrace negativně ovlivňuje výsledky vzdělávání CLB, kdy ovlivněni jsou především chlapci. V případě dívek není nalezen žádný významný vliv. Navíc zjišťujeme, že použití binární dummy proměnné pro migraci, jako je tomu v předcházejících studiích, vytváří pozitivní zkreslení IV odhadu přibližně na trojnásobek své hodnoty. Naproti tomu míra intenzity migrace dává přesnější výsledky.

Working Paper Series ISSN 1211-3298 Registration No. (Ministry of Culture): E 19443

Individual researchers, as well as the on-line and printed versions of the CERGE-EI Working Papers (including their dissemination) were supported from institutional support RVO 67985998 from Economics Institute of the CAS, v. v. i.

Specific research support and/or other grants the researchers/publications benefited from are acknowledged at the beginning of the Paper.

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Published by Charles University, Center for Economic Research and Graduate Education (CERGE) and Economics Institute of the CAS, v. v. i. (EI) CERGE-EI, Politických vězňů 7, 111 21 Prague 1, tel.: +420 224 005 153, Czech Republic. Printed by CERGE-EI, Prague Subscription: CERGE-EI homepage: http://www.cerge-ei.cz

Phone: + 420 224 005 153 Email: office@cerge-ei.cz Web: http://www.cerge-ei.cz

Editor: Byeongju Jeong

The paper is available online at http://www.cerge-ei.cz/publications/working\_papers/.

ISBN 978-80-7343-448-9 (Univerzita Karlova, Centrum pro ekonomický výzkum a doktorské studium) ISBN 978-80-7344-501-0 (Národohospodářský ústav AV ČR, v. v. i.)