Final Report

Working paper version

The effect of parental migration on the schooling of children left behind in rural Cambodia

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May 2019

pep partnership for economic policy

PAGE policy analysis on growth and employment

IDRC CRDI

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Abstract

This study uses three waves of household survey from 11 rural villages in Cambodia collected in 2011, 2014, and 2017 by the Cambodia Development Resource Institute (CDRI) to examine the effects that parental migration had on the educational outcomes of left-behind children. Using a propensity score matching (PSM) approach, the study finds that parental migration has significant negative impacts on the years of schooling of the left-behind children, especially older children. It reduced the completed years of schooling by about half a year, while the migration of brothers or sisters of the children, when parents are at home, has no effect on the education of the home children. Falsification testing provides proof that the effect in our model is really a causal effect. Our results also show a similar pattern of impact on schooling outcomes for both boys and girls.

Keywords: Cambodia, Parental migration, Remittances, Education, Child schooling

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Acknowledgements

This research work was carried out with financial and scientific support from the Partnership for Economic Policy (PEP) with funding from the Department for International Development (DFID) of the United Kingdom, and the Government of Canada through the International Development Research Center (IDRC). The authors are very grateful to Professor Francesca Marchetta for overall technical support and guidance, and to Professor Simone Bertoli for technical guidance during the authors' study visit to France. Thank you to various stakeholders for participation in the consultation meetings and workshops, and to CDRI colleagues for their valuable comments and suggestions.

Contents

1. Introduction

Migration, whether internal (within the country) or international, has been remarkable in Cambodia during the past decade owing to the urbanisation, Phnom Penh in particular. Tremendous development of various industries, including garment and textile, real estate, hotel and construction, has concentrated low-skilled labour demand in Cambodia, as it has elsewhere across Asia (Hing et al, 2014 p.2). The topic has been emphasised by policy makers and researchers, as well as stressed in Cambodian government policy documents including the National Strategic Development Plan (NSDP) 2014-2018 and the Policy on Labour Migration for Cambodia in 2010.

The NSDP 2014-2018 clearly indicates the government's intention to reduce rural to urban migration by investing in rural water, transport and power infrastructure which are expected to generate employment opportunities and promote local community development in rural Cambodia (RGC, 2014a p.143). At the same time, the Policy on Labour Migration for Cambodia introduced in 2010 aims instead to promote international migration and to protect Cambodian migrants residing in the host countries. Yet it does not outline steps to support the children and elderly left behind by such migration.

Besides the Ministry of Labour and Vocational Training (MoLV), migration from rural areas has caused concern on other ministries. The Ministry of Agriculture, Fishery and Forestry (MAFF) has shown concern that the decrease of rural labour will affect agriculture production and country food security. The Ministry of Education Youth and Sport (MoEYS) has long voiced on the consequences of parents migration on child education, especially further human capital and social problem.

Given the substantial rise in interest among policy makers and researchers in these topics, several studies have been conducted to explore the causes and consequences of rural-urban and international migration in Cambodia; Chan (2009), IOM (2010), and Hing et al. (2010 & 2011) showed anecdotal evidence regarding the push and pull factors of migration in Cambodia , while more recent empirical studies have focussed on migration's impact on poverty reduction Tong (2012) and Roth and Tiberti (2016), who confirm the poverty-reducing role of migration.

Yet research on migration and human capital formation in Cambodia is sparse and not rigorous. Hing et al. (2014) used the Socio-Economic Survey 2009 (CSES) and applied instrumental variable (IV) methods to investigate the effect of migration on education, labour and health of children. They found a negative effect on school attendance and health among children, but their IV estimates for both outcomes (school attendance and years of schooling) are not statistically significant. OECD (2017) investigated the impact of migration on household education expenditure in eight provinces in Cambodia. The study included both binary treatment variables (e.g. remittances and migrant) in its estimation equation. It found that remittances increased education spending, while migration (absence of adults from household due to migration) reduced it. However, the study did not address endogeneity problems, leaving uncertainty for causal interpretation.

Importantly, these studies did not consider the relation between the migrant and the children left-behind, instead using household-level migration data which does not accurately support investigations on the effect on child education. Thus, this study is intended to fill this gap by applying propensity score matching, like in Zhou, Murphy et al. (2014) to investigate the relationship between parental migration and human capital formation.. We thus explore how parental absence due to migration affects child education.

Intuitively, there are two channels through which migration potentially affects child schooling; remittances, by relaxing household credit and budget constraint by increasing household income and allowing households to invest in children education (Hanson and Woodruff, 2003); and absenteeism of working-age adults who migrate to search for a job, which makes households more likely to keep children out of school due to household chores or farm work (Bansak and Chezum, 2009). In addition, absence of working age parents could also disrupt human capital formation through a reduction in inputs of children education production (Giannelli and Mangiavacchi, 2010).

International studies on the impact of migration on human capital formation, particularly in child schooling, have revealed two lines of evidence based on the type of treatment variables that were used. The two commonly used treatment variables of migration include remittances and number of migrants who were absent from households. Remittances are found to increase schooling of school-age children (Hanson and Woodruff, 2003; Edwards and Ureta, 2003; Mansuri, 2006; Calero et al., 2009; Bansak and Chezum, 2009; Antman, 2012; Hu, 2012), while absence of migrants is found to reduce educational attainment of school-age children (McKenzie and Rapoport, 2006; Lu and Treiman, 2007; Bansak and Chezum, 2009; Giannelli and Mangiavacchi, 2010; Hu, 2012).

Hanson and Woodruff (2003) examined the impact of migration to the United States on educational attainment of left-behind children aged 10-15 in Mexico, by using a micro 10 percent census of population and housing in 2000. They used binary treatments of migration and remittances in separate estimation equations and found positive impact of both alternative treatments on years of schooling for boys and girls. This study attributed the impact to the increase in household income from remittances. Also in Mexico, Atman (2012) used several waves of household survey from Mexican migration projects, and exploited the variation in the age of children at the time their father migrated within Mexico and to the US to identify the impact of migration on educational attainment of children aged 0-19. The study did not find any effect of a father's migration within Mexico on schooling for boys and girls, but did find a positive and statistically significant effect of father's migration to the US on girls' educational attainment.

In other settings, such as El Salvador, Edwards and Ureta (2003) found that children from the remittance-receiving households were more likely to stay longer in school than those from the non-recipient households. Similar evidence from other settings includes Mansuri (2006) in Pakistan, Calera et al. (2009) in Ecuador, Mansour et al. (2011) in Jordan, Bansak and Chezum (2009) in Nepal, and Hu (2012) in China.

However, despite a growing body of literature that shows a positive effect of migration on education of children, several studies have revealed contradicting findings. Giannelli and Mangiavacchi (2010) used a Living Standard and Measurement Survey in 2005 to look at the long-term impact of parental migration on schooling of left-behind children in Albania and found that past parental migration reduced school attendance and increased the probability of dropping out of school of the children left-behind. The study attributes the effect to the lack of parental care owing to parental absence from household. Additionally, in rural Mexico, McKenzie and Rapoport (2006) used a national survey of demographic dynamics in 1997, and binary treatment of whether households had a migrant member, and also found that migration had a negative effect on schooling attendance and attainment of boys aged 12-18 and girls aged 16-18. In South Africa, Lu and Treiman (2007) showed that children from migrant households without remittances were less likely to be enrolled than those from remittance receiving households.

Remittance and migration are two different things. A few studies have tried to separate the effect of the two including Bansak and Chezum (2009) and Hu (2012). They included both remittances and absence of migrants in their estimation equations and can only show the positive effect of the former treatment and negative effect of the later on educational attainment of children in their respective countries. Therefore, the net effect of migration on child educational attainment is unclear. It is difficult or even impossible to separate the effects of remittances and the absence of migrant household members on the education of children left behind, as demonstrated by by Bertoli and Marchetta (2014).

Therefore, this study will investigate the impact of parents' migration on child educational outcomes. No well-identified studies in Cambodia have yet shown the robust effect of migration on child schooling in the country. Hing et al (2014) examined the effects of migration, but did not control for remittances in their regression equation, and they were unable to provide causal interpretation of the effect of migration on child educational outcomes. This study also provides a new perspective for the setting of Cambodia regarding how parents' migration affects educational outcomes of left-behind children. Nonetheless, limitations regarding the generalisation of the findings from this study provided that data used in this study covers only 11 rural villages in Cambodia. Therefore, one should caution when designing interventions for tackling this problem on a nation-wide scale.

The next section provides an illustration of Cambodian education and migration situation, followed by a discussion on the empirical method used to quantify the effect of parents' migration on children education outcomes. Section 4 presents data used for the analysis and Section 5 presents findings followed by the conclusion.

2. Cambodian education and migration situation

2.1. Education in Cambodia

General education in Cambodia consists of 12 years of schooling, which is categorised into primary education (6 years), lower-secondary (3 years) and upper-secondary education (3 years). The 6-year primary education system followed reform in 1996, as set out in the Cambodian constitution, which states that Cambodian children aged 6 and above are entitled to a free basic 9-year education.

Accoring to MoEYS, the rural net enrolment rate for primary education for the 2014-15 school year[1] was 96.5 percent, higher than the 83.3 percent in urban areas (table 1). suggesting that there were a number of children at age 6 did not enrol in grade 1. It is called late enrolment beyond standard age. Gross enrolment rates for lower and upper-secondary school in rural Cambodia are also low at 53.3 per cent (55.8 in urban) and 20.2 per cent (39.4 in urban) respectively. In addition to late enrolment, average drop-out rate for grade 1 to 6 in rural areas was also high at 6.6 percent and repetition rate at 7.2 percent in 2014-15 (table 2). As a result, child education in rural area is a few years lower than the standard year. For example, at age 12, they supposed to complete primary education (grade 6). But in rural areas, the average age for completing grade 6 is 15 years old (CDRI data), which is 3 years late. Rural drop-out rates for lower- and upper-secondary education were even higher at 20.6 and 26

[1] We use 2014-15 school year because our main analysis uses 2014 data.

percent, respectively. High drop-out rates at secondary education suggests that the country is grappling with a challenge to increase the level of its human capital in rural areas.

Table 1: Gross and Net Enrolment Ratios 2014-15

	Gross Enrolment			**Net Enrolment**
	Primary Level (Grades 1-6)	Lower Secondary Level (Grades 7-9)	Upper Secondary Level (Grades 10-12)	Primary Level (Grades 1-6)
Urban Area	93.6	55.8	39.4	83.3
Rural Area	113.5	53.3	20.2	96.5

Source: MoEYS 2015

Table 2: Student Flow Rates and Graduates by level for Both sex 2014 -2015

	Primary Level			**Lower Secondary Level**			**Upper Secondary Level**		
	Promotion	Repetition	Dropout	Promotion	Repetition	Dropout	Promotion	Repetition	Dropout
Urban Area	90.9	4.6	4.5	82.7	3.2	14	76.5	3.7	19.8
Rural Area	86.3	7.2	6.6	77.4	2	20.6	71.1	3	26

Source: MoEYS 2015

There are a range of demand- and supply-side factors underlying the low secondary enrolment rate and high secondary drop-out rate in rural Cambodia. For instance, demand-side factors include poverty, migration (i.e. rural-urban and international), education of the head of the household, demand for household chores and farm work (mainly agricultural activity), being short-sighted, and health problems and malnutrition[2].Supply-side factors consist of geographical locations and conditions such as distance to school (RGC, 2015; RGC, 2014b; Ban & Kim, 2015; Fata & Hirakawa, 2012; Keng, 2005).

2.2. Migration situation in Cambodia

Cambodia's consistent economic growth in the past decade has had a large impact on urban areas, leaving many rural areas behind. Nearly one quarter of the Cambodian population of 16 million has migrated from their villages looking for better opportunities (UNESCO 2018). Internally, the majority of migration (58.4%) is rural to rural, with rural to urban and urban to urban representing 24.5% and 12% respectively.

Despite their different destinations, most migrants have a similar background. According to a study conducted by Kimchhoy, Federico et al. (2016), the majority of potential migrants had not completed lower secondary school, had a low monthly net income of approximately 25 USD, and had personal debt of over 10 USD. Interestingly, gender does not appear to be a significant factor in migration in general (UNESCO 2018), though the female spouse is more likely to be left behind than the male if there is a child to take care of (Kimchhoy, Federico et al. 2016).

Kimchhoy, Federico et al. (2016) showed that 81 percent prefer to migrate internally though there are other factors such as location, salary, position, and family ties that influence where someone will choose to migrate. While nearly half of rural migrants move to Phnom Penh, others travel to the smaller Cambodian cities of Battambang, Kampong Cham, and Siem Reap (which might be closer to their home villages). Migrants do sometimes choose to migrate internationally for work, especially those who live close to the Thai border. While abroad, they will typically work in the fishing, agriculture, livestock, construction, manufacturing, and services sectors (ILO 2019). It is difficult to estimate the true number of migrants as many do so illegally, but the IOM estimate there are 650,000 Cambodians working in Thailand The official records published by the UNDESA (2017) show that only 76,000 people migrated from Cambodia in 2017 and that Cambodian migration has been dropping overall compared to past migration and as share of total migration. Based on the study by Kimchhoy, Federico et al. (2016), however, nearly 200,000 illegal migrants were deported from Thailand in 2014 alone, showing that official number do not provide the whole story. To try and regulate migration, the Royal Government of Cambodia has signed a number of agreements on labour migration with countries including Thailand, Malaysia, South Korea, Singapore, Kuwait, and Saudi Arabia, all of which with varying levels of impact.

Several studies show the push and pull factors of migration in Cambodia (Maltoni 2006; Chan 2009; IOM 2010). Push factors for migration are poverty, lack of employment, lack of alternative sources of income, landlessness, inability to access to markets, debt and natural disasters. Pull factors include wage differentials, geographical proximity and migrant networks. According the Cambodia Rural-Urban Migration Project (CRUMP) conducted by the Ministry of Planning (MoP) in 2012, the main reason for migration is labour-related reasons (85 percent of migrants to Phnom Penh and 97 percent internationally). A qualitative study by UNICEF (2014) found that financial realities and loans are the main reasons for migration in Cambodia. Worsening conditions in rural communities ensure that agricultural productivity, on average, is barely increasing while land is being subdivided among children every generation, leaving families with smaller plots of land to support themselves.

In addition to these powerful push factors, there are a number of pull factors which influence the destinations of migrants; access to a wider variety of industries and higher salaries being of primary importance. For those who stay in Cambodia, a higher sense of personal security and a desire to remain close to families is important, while those who migrate externally typically do so due to a perception of higher salaries outside of Cambodia, (despite the lower perceptions of living conditions). It is important to note that poor living conditions are one of the top three reasons that migrants choose to return home.

Itis challenging to determine how much money migrants actually make. Internally, the average monthly wage is 119 USD (Kimchhoy, Federico et al. 2016). In Thailand, Malaysia, and South Korea, the minimum monthly wages are 9,000 baht (260 USD), 900 ringgits (295 USD), and 860,200 won (734 USD) respectively. While these minimums are clearly higher than the average in Cambodia, it is unlikely that migrants actually receive these amounts due to exploitation, extended hours and underpayment. Planning (2012) reported that nearly all migrants remitted a proportion of their income to their families. Migrants in Phnom Penh remit a larger portion of their income than migrants in other urban locations since they are usually better educated and earn more. Furthermore, migrants in the garment industry remit about 25% of their income -- larger than migrants in other industries such as construction, entertainment, education and small business.

The influence of family on all stages of the migration process cannot be overstated. One of the main reasons that some Cambodians do not migrate for work is their obligation to take care of family members. Additionally, the suggestions from friends and family have the highest influence on where they choose to migrate to and homesickness is another of the top three reasons that migrants return home.

When Cambodians migrate for work, they often leave behind family members, such as a spouse, child, sibling, parent, or some combination thereof. The children who are left behind are typically the ones most at risk in these situations;21.1 percent of all migrant households have at least one child under 18 that has been left behind (Zachary and Meredith 2015). The most common household structure in this situation is the child of a migrant plus the spouse of the migrant. Yet, nearly half of the children under 18 who are left behind are living without parents, with nearly one quarter living without a parent or a grandparent, and 1.7 percent not living with any relative. The Planning (2012) found that 82.4 percent of domestic migrants who left children behind left their children with grandparents (usually a grandmother). UNICEF's (2014) qualitative study reports that most caregivers of left-behind child were grandparents averaging 62 years old and with limited to no formal education.

Overall, migrant Cambodian households barely differ socioeconomically compared to their non-migrant counterparts, but there are a few caveats (Zachary and Meredith 2015). It is rare for non-migrant households to skip a generation, whereas almost 7 percent of migrant households do. This is a very risky financial situation because households without adults are on average worse off than households with adults given that adults are typically the breadwinners.

3. Methodology

3.1. Propensity score matching

Ideally this study would test the effect on education performance of children being left behind and while still with their parents. However, that is impossible and we therefore compared children with similar individual and family characteristics to compare the effects of parental migration on education. Following the work of Bertoli and Marchetta (2014), this study employs propensity a score matching (PSM) approach. There are other estimation techniques including instrument variable (IV), however, it is hard to find a credible instrument for parental migration and the PSM technique does not require the introduction of assumptions on the functional form of the relationship between household characteristics, migration and educational outcome. We have been careful about the biased estimation of PSM, and therefore performed biased-adjustment tests and robustness checks.

PSM matches the treated and untreated observations on the estimated probability of being treated (the propensity score). The propensity score is the probability that a unit will enrol in the program based on the observed values of its characteristics. This score is a real number between 0 and 1 that summarises the influence of all of the observed characteristics on the likelihood of being treated. The propensity score:

$$P(X) = Pr\,(d = 1|X)\,D \qquad (1)$$

indicates participation in project. Instead of attempting to create a match for each participant with exactly the same value of X, we can instead match the probability of participation. The key assumption of PSM is that participation is independent of outcomes conditional on X_i as:

$$y_0 \coprod z|f(x), \qquad (2)$$

where z is assigned to treat, y_0 represents outcome when z_i = 0, and $f(x)$ is the probability of assignment to treatment or propensity score. Or:

$$E_T[y_{i0}|z_i = 1, f(x) = p] = E_U[y_{i0}|z_i = 0, f(x) = p] \quad (3)$$

Thus, average treatment effect on the treated (ATET) can be estimated as:

$$\hat{E}_T(\tau_i|z_i = 1) = \int_0^1 (E_T[y_{i0}|z_i = 1, f(x) = p] - E_U[y_{i0}|z_i = 0, f(x) = p])g(p)dp, \quad (4)$$

where $g(p)$ is the distribution of the propensity score over the subsample T.

3.2. Implementation of PSM

To implement the PSM, we follow Caliendo and Kopeinig's (2008) practical guidance; estimating the propensity score; choosing a matching algorithm; checking over-lap/common support; matching quality/effect estimation; and lastly the robustness check. In our model, the treatment is children that have parents who have migrated and the outcome is presented by the years of schooling of the children left behind.

Estimating the propensity score

There are two steps in estimating the propensity score; one concerns choosing the model for the estimation, and the second is choosing covariates to be included in the model. Since our treatment is binary variable, we use logit model and the probability of assignment to the treatment is estimated as:

$$f(x) = \frac{e^{x'\beta}}{1+e^{x'\beta}} \quad (5)$$

Section of the covariates

The next step is to decide on the inclusion or exclusion of covariates in the logit model. A set of variables X should be included only if they simultaneously influence the participant decision and the outcome variable (Caliendo and Kopeinig 2008). The estimation of the propensity score is to estimate propensity score to serve as a balancing score, and it is not about to maximise the fit of the logit model. Thus, it is ideal to include X that exclusively influences the treatment because it would reduce the balancing score.

To avoid any endogeneity with respect to the exposure to the treatment itself, X variables should either be fixed over time or measured before participation.

Choosing a matching method

There are a number of matching methods for PSM estimators. The matching estimators differ by the definition of neighbourhood for each treated individual and the handling of common support. It is not feasible to estimate ATET on the exact matching on $\hat{f}(x)$ in equation (4). Thus, we employ nearest neighbour (NN) matching. Given the small sample of treatment group, we use *n*-NN matching with replacement.

Check for the balancing property

ATE is defined only in the overlapping or region of common support. We follow Bertoli and Marchetta (2014) and re-estimate the propensity score on the matched sample between treated and matched controls to test the balancing property. The pseudo-R^2 on the matched sample should be small, thus suggesting no difference between matched control and treated characteristics. As in Bertoli and Marchetta (2014), we also compute the ATET with the adjustment for bias introduced by Abadie, Imbens et al. (2004). When matching is not strictly 1-to-1, the matching estimator will be biased and the bias-adjusted estimator will adjust the residual imbalance of the covariates.

4. Data

This study uses three waves of panel household survey collected by CDRI in March 2011, March 2014 and March 2017. The same 11 villages were used in each wave. The villages were selected based on their rural location and stratified by four geographical zones; the Mekong and the Tonle Sap plains, the upland plateau, and the coastal zone. The survey collected both household and village information and the questionnaires cover household demographic information, migration, education, health, employment and occupation, housing, durable assets, land ownership, credit, income, consumption, access to common property resources, environmental shocks, and development programs[2].

There were 1,142 households in 2011. In 2014 1,182 households were included, and 1,103 in 2017. The attrition rate of each wave was around 10 percent[3] and, in each wave, new households were selected to replace the dropouts. The data of the three waves is in the form of household panel data. However, for our analysis, we were able to construct a person panel of the three waves using individual information in the data[4].

In this study, we defined migrant by considering place and purposes. We define as international migrants as whoever left the original household and resided abroad[5]. For internal migrant, we follow Roth and Tiberti's (2017) definition as someone who left the household of origin to take or look for a job in a province other than their own[6]. We define 'left' as those individuals who moved to other parts of Cambodia for other reasons than migration (mostly marriage)[7].

Since we want to investigate the outcome at the child level, the data was constituted by children. There are 2,418, 2,090, and 1,833 children in the study from 2011, 2014 and 2017 respectively.

To be able to identify the mother and father of a child, we restrict our sample to only children or grandchildren of the household head, 98 percent of the children of target age 6 to 19 years old in the study are children or grandchildren of household head. In total, 2,090 children aged between 6 to 19 years for 2014 wave were sampled, but as our analysis focuses on left-behind children or children at home, we dropped migrant children and thus, 1,934 children are used for 2014 data.

[2] Please refer to annex table A2 for descriptive statistic of main variables comparing with national data
[3] Please refer to annex table A3 for descriptive statistic of main variables comparing with missing households
[4] The individual panel was constructed by first merge the three waves households by household ID (household level). Second, we manually identified the same individuals within the panel households using all of individual information started with name, sex, age, relationship with household head, and education level.
[5] In the questionnaire, if the individual replied 3 or 4 to question 8, annex table A1.
[6] In the questionnaire, section 1, part B, question 8, the answer is 1. Phnom Penh or 2. other part of Cambodia and question number 10, the answer is 1. To take a job Or 2. To look for a job Or 3. To study.
[7] It will appear in our categories of parent with label as "Left".

Outcome variables: We use main educational outcomes that are commonly used in the literature as a measure of human capital of children in household. The eligible age for enrolment is 6, thus, we use an age window between 6 and 19. Outcome variable is the number of t years of schooling completed by children aged 6-19 at a given period (survey round).

Treatment variables: We considered a number of treatment variables. First is if either parent (mother or father, or both) migrated internationally. We first focus on international migration and then on internal migration. Second is if either parent migrated internationally or internally. Third, the absence of a parent including by death, divorce, and migration is treated to highlight anydifferentials between the effect of absence of parents and migrant parents. Lastly, children who have parents at home but other members have migrated. These treatments are to investigate the effect of non-parent migrants and their remittances.

List of treatment variables:

1. Either parent migrated:	1 if either mother or father or both parents of the child migrated internationally, else 0
2. Either parent migrated internally	1 if either mother or father or both parents of the child migrated internationally or internally, else 0
3. Absent either parent:	1 if either mother or father or both parents of the child absent, else 0
4. No parents migrated but other members did	1 if any member of household migrated internationally or internally but both parents were at home

Control variables: Identification of covariates is important in PSM. As mentioned in the methodology, control variables must influence both the probability of having parental migration and influence on the child education outcomes (Caliendo and Kopeinig 2008). Thus, we included household characteristics before treated such as household size, number of working members, ratio of dependency, and share of working women; household assets in 2011[8]; mother and father characteristics such as age and education; child characteristic such as age and sex. Since there is no data available, we cannot include distance to school as supply side variable, we used village dummy.

4.1. Descriptive statistics

Table 3 shows the relevant descriptive statistics of children with migrant parents and no migrant parents and the whole children sample. 'Years of schooling 2014' is the outcome variable of interest, and the rest are variables that need to be controlled since they could influence both the parents' migration behaviours and child education. It is interesting to note that migrant parents are on average younger than parents that are not migrants. It also affects the average education of non-treated parents since most of older rural people have no education. Household size, number of working members, dependency ratio, and share of working female variables are pre-migration variables except asset. Assets are the 2011 asset index.

[8] Unfortunately, household asset in 2011 is not really a pre-treated variable, since some migration happened before 2011. To overcome this challenge, we did robustness test in result section by dropping asset 2011 from model.

Table 3: Descriptive statistics

	Children		
Variables	Treatment (Either parent migrant)	Non treated	All
Years of schooling 2014	2.43	4.02	3.91
	(2.11)	(3.02)	(2.99)
Assets in 2011	22.59	24.72	24.58
	(12.58)	(15.02)	(14.88)
Household size	6.46	6.21	6.23
	(2.30)	(2.01)	(2.03)
Number of working	3.28	3.68	3.65
	(1.41)	(1.56)	(1.56)
Dependency ratio	1.18	0.87	0.89
	(0.89)	(0.71)	(0.73)
Share of working female	0.52	0.62	0.62
	(0.24)	(0.26)	(0.26)
Age of mother	33.68	42.20	41.64
	(6.68)	(8.70)	(8.83)
Mother's education	3.53	2.79	2.84
	(3.24)	(2.58)	(2.63)
Age of father	33.02	44.25	43.51
	(6.82)	(9.13)	(9.42)
Father's education	5.14	3.86	3.95
	(3.94)	(3.12)	(3.20)
Sex	0.46	0.53	0.53
	(0.50)	(0.49)	(0.49)
Age	10.47	12.72	12.57
	(3.15)	(3.85)	(3.85)
Observation	127	1,807	1,934

Source: Author calculation. Standard deviations in parenthesis

Figure 1: Mean of years of schooling age, entire sample

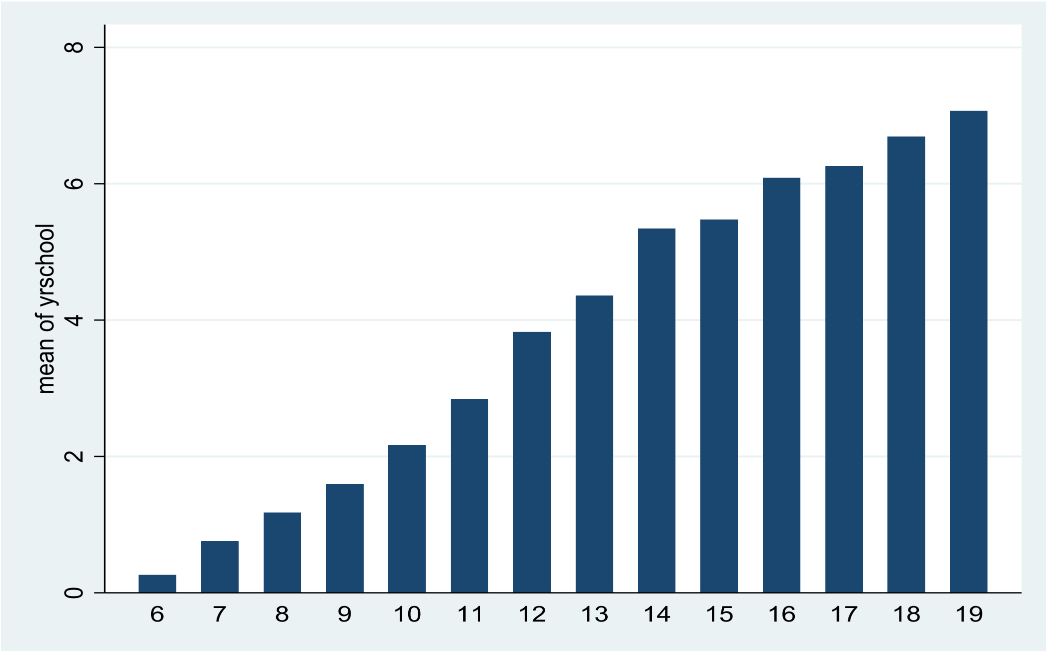
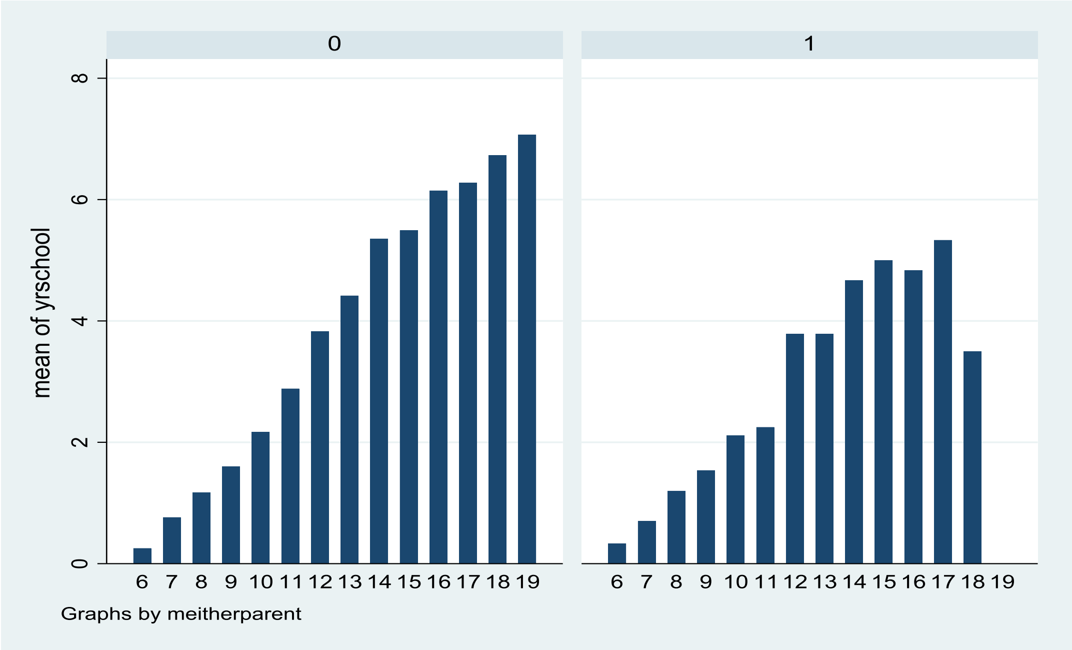


Figure 2: Mean of years of schooling by children who have either parent as a migrant (1) and non-migrant (0)



Source: Author calculation

Figure 1 and 2 report average years of schooling of sample children by age. On average, only a few children completed primary education. They are lower than the Cambodian standard years of schooling, where at age of 13 they are supposed to have completed grade 6. However, in our sample the children only completed grade 4. A possible explanation is that our sample children are located in rural areas where there is late enrolment and a lot of repetition of grades. More significantly, mean years of schooling for treatment children (who had either parent as a migrant internationally or internally) are below non-treated children, especially of older children.

4.2. Hypothesis on Mother and Father

As explained, we restricted our sample to children and grandchildren of household heads. For children of household heads, identifying their mother and father is easy and direct. However, since our data only realates to household heads, to identify the mother or father of a grand-child (18 percent of the total sample) is not direct. Thus, for those 18 percent, we need a few assumptions to identify their possible parents[9]. Table 4 shows the distribution of children in our sample by their parents' status. Eighty-one percent of children in the sample have both parents at home.

Table 4: Distribution of children in the survey sample by parents' status

	No Mother	Home Mother	Left-mother	Internal migrant mother	International migrant mother	Total
No father	10	121	3	3	2	139
Home father	22	1,579	10	9	2	1,622
Left father	8	27	27	6	7	75
Internal migrant father	3	17	1	10	2	33
International migrant father	4	25	8	3	25	65
Total	47	1,769	49	31	38	**1,934**

Source: Author calculation

5. Results

5.1. Main Results

Table 5 reports the results of matching estimates of the effects of the migration of either parent on left-behind children on years of schooling with nearest neighbour matching, with a number of matches n = 1,

[9] First, we assumed any married women/men living in the household to be mother/father of the grandchildren. If any married woman/man at home exists, she/he is the mother/father. We think if there are any married woman/men at home, she/he can replace the parent, even if they are not the child's real parents (and likely an aunt/uncle). If no married woman/man at home, then we look at a possible mother among migrants. If a married migrant exists, then we suppose that she/he is the mother/father of the child. In case that no married person is at home and no married among migrants, but mother/father left (moved out) then she/he is the mother/father of the child. Lastly, if no married woman/man at all in the family, then the child has no mother/father, in which case they are likelydead or divorced.

2,…,n[10]. The years of schooling of children with migrant parent internally and internationally range between 0.4 to 0.5 years lower compared to that of matched children with both parents at home. This suggests that the absence of either a mother or father (or both parents), due to migration reduced years of schooling completed of left-behind children. Pseudo-R^2after matching is low, reassuring the balance of treated and control children characteristics. We test our model with treatment variable of either parent being an international, and the result is almost identical (table 6).

It is astounding that with all else being constant, the migration of either parent from a household reduced the years of schooling of left-behind children by about half a year, which is substantial. We further tested where the absence of either parent was due to other reasons including death, divorce, or migration as a treatment (absent either parent treatment variable). The result shows further negative effects of the absence of a parent on a child's years of schooling (table 7). It is possible that the absence of a parent due to migration is partially offset with remittances[11], but any positive remittance effect is less than the negative effect of the parent's absence.

The results confirm some literature on the lack of parental supervision and mental support for left-behind children, and the substitution of adult labour with left-behind child labour due to migration could be an underlying mechanism of the disruption of child education.

Table 5: The effect on Years of schooling in 2014 (children with either migrant parent both international and internal)

n	m_eitherparent	Matched control	Pseudo-R2	ATET	ATET bias-adj.
1	119	83	0.08391204	-0.3418803	-0.1334317
				(0.3549949)	(0.2291961)
2	119	140	0.04903389	-0.3846154	-0.328363
				(0.3321291)	(0.1828435)*
3	119	189	0.0392461	-0.3931624	-0.4635093
				(0.3106116)	(0.1910224)**
4	119	235	0.03376358	-0.3376068	-0.4554003
				(0.2907444)	(0.1775383)**
5	119	279	0.02559737	-0.3350427	-0.4809497
				(0.2806991)	(0.1679877)***
6	119	313	0.01740429	-0.3803419	-0.4819354
				(0.2802757)	(0.165039)***
7	119	343	0.01294181	-0.3479853	-0.4815699
				(0.2808421)	(0.1635321)***
8	119	369	0.01271204	-0.4401709	-0.5002245
				(0.2899112)	(0.1636644)***
9	119	393	0.01215908	-0.4140551	-0.4881371
				(0.2859063)	(0.1613136)***
10	119	409	0.01284324	-0.3769231	-0.4900326

[10] The estimation of the propensity score, logit model, was reported in annex table A3.
[11] 83 percent of children with either migrant parent received remittance.

				(0.281284)	(0.1577586)***

Notes: Standard errors are in parentheses; *** p < 0.01, ** p < 0.05, * p <0.10; n represents the number of nearest neighbours used in the matching; the pseudo-R^2 is derived from the re-estimation of propensity score on the sample of matched children only.

Table 6: The effect on Years of schooling in 2014 (children with either parent migrant internationally)

n	int_eitherparent	Matched control	Pseudo-R2	ATET	ATET bias-adj.
1	77	49	0.07593216	-0.0133333	-0.4982504
				(0.4346298)	(0.3186877)
2	77	87	0.05997779	0.2266667	-0.3962189
				(0.3970607)	(0.2309234)*
3	77	119	0.06284455	0.1955556	-0.3092469
				(0.3808948)	(0.2220793)
4	77	146	0.05581656	0.1066667	-0.4067204
				(0.3793639)	(0.2147687)*
5	77	168	0.05099933	-0.0773333	-0.4748865
				(0.3785534)	(0.2071432)**
6	77	189	0.04834572	0.0066667	-0.4509134
				(0.3698287)	(0.2032598)**
7	77	209	0.04309737	0.0152381	-0.4179809
				(0.3649)	(0.2052109)**
8	77	228	0.04093562	-0.025	-0.4227963
				(0.362074)	(0.201883)**
9	77	244	0.03521034	-0.0637037	-0.4463621
				(0.3614084)	(0.2023756)**
10	77	261	0.03394651	-0.06	-0.4297945
				(0.358214)	(0.2012661)**

Notes: Standard errors are in parentheses; *** p < 0.01, ** p < 0.05, * p <0.10; n represents the number of nearest neighbours used in the matching; the pseudo-R^2 is derived from the re-estimation of propensity score on the sample of matched children only.

Table 7: The effect on Years of schooling in 2014 (children with absence of either parent)

n	m_aeitherparent	control	Pseudo-R2	ATET	ATET bias-adj.
1	330	232	0.01852626	-0.3957055	-0.5671674
				(0.2794935)	(0.1719776)***
2	330	406	0.01262692	-0.5623722	-0.6068695
				(0.2437641)**	(0.1554061)***
3	330	549	0.00864182	-0.6303681	-0.6287942
				(0.2339166)***	(0.1436196)***
4	330	663	0.0087782	-0.565184	-0.6253913
				(0.224158)**	(0.1358731)***
5	330	750	0.00633344	-0.6198364	-0.6088497
				(0.2183604)***	(0.1329376)***
6	330	830	0.00720534	-0.5629565	-0.6130247

				(0.2140022)***	(0.1325471)***
7	330	896	0.00680094	-0.5458175	-0.6179269
				(0.2114208)**	(0.1311182)***
8	330	956	0.00721704	-0.5233044	-0.6264137
				(0.2101632)**	(0.1293172)***
9	330	1005	0.00792769	-0.516394	-0.6317244
				(0.209315)**	(0.1283398)***
10	330	1044	0.00732109	-0.5156442	-0.6226023
				(0.2078695)**	(0.128319)***

Notes: Standard errors are in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$; *n* represents the number of nearest neighbours used in the matching; the pseudo-R^2 is derived from the re-estimation of propensity score on the sample of matched children only.

To check the effect of migration of any member of the household on their child's years of schooling, we tested our last treatment variable; any member a migrant except parents of children. Besides parents, migrants are mostly brothers or sisters of the children being studied. The test did not significantly suggest an effect of another family member besides parents on children years of schooling (table 8). However, we found an interesting sign of the coefficients of the test. When parents are at home only and other family members are migrants, the coefficients are positive[12]. The result indicates that when it is not the parents who migrate, there is no negative effect on education of the children. This can be explained by the fact that the parent is not absent. At the same time, we also see that there is not a positive effect (of remittances) on education. Or, if it exists, it is probably compensated by the child's house and farm work. Thus, the remittances might have been used by households with left-behind children for other purposes than investment in education, such as food, because average remittances might not be sufficiently substantial for households to cover items beyond their food needs. Importantly, our other conjecture is that rural farm households are usually myopic and do not understand the importance of investment in human capital of their next generation. Additionally, child labour in agriculture is quite common in rural Cambodia, and the use of remittances to pay for hired labour instead of using household children may not be likely.

Overall, our results strongly indicate that there is disruption of education of left-behind children as a result of parental migration, while at the same time children with absent parents due to reasons other than migration have even higher disruption of education. It might suggest a small effect of remittances from migrant parents on compensating for the loss of schooling of left-behind children. Our results, though based on a unique and context-specific panel data from 11 rural villages in Cambodia, provide new insights into the effect of parental migration on educational outcomes of left-behind children. This clearly indicates that in the setting of the 11 rural villages that parental migration disrupts schooling of left-behind children, and suggests the negative long-term implication of migration on livelihood, welfare, as well as economic development of these 11 rural communities if the trend continues.

[12] At least for the bias-adjust.

Table 8: The effect on years of schooling in 2014 (children in the household that have no parents migrant but have other member migrant)

n	m_noparentbutother	Matched control	Pseudo-R2	ATET	ATET bias-adj.
1	608	223	0.03312438	-0.2414414	-0.1574295
				(0.2864047)	(0.1826767)
2	608	362	0.02440334	-0.1216216	0.0059741
				(0.2603706)	(0.164201)
3	608	454	0.02346999	-0.0828829	0.0794287
				(0.2502766)	(0.1599079)
4	608	519	0.02622042	-0.1162162	0.0675083
				(0.2466173)	(0.1578983)
5	608	564	0.0239976	-0.1227284	0.0762809
				(0.2442153)	(0.1573911)
6	608	599	0.02097371	-0.044616	0.1201376
				(0.242605)	(0.1572176)
7	608	637	0.0210753	-0.0764479	0.1005243
				(0.2396001)	(0.1554189)
8	608	669	0.01997204	-0.0623874	0.1214744
				(0.2379087)	(0.1540766)
9	608	691	0.01806808	-0.0954354	0.095959
				(0.23828)	(0.1543201)
10	608	716	0.01699823	-0.1284685	0.0864212
				(0.2395301)	(0.1539761)

Notes: Standard errors are in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$; *n* represents the number of nearest neighbours used in the matching; the pseudo-R^2 is derived from the re-estimation of propensity score on the sample of matched children only.

5.2. Robustness check

A robustness check is crucial to check the estimated results from hidden bias, and checks on the medium-term of outcome variables, falsification tests, and other children-age filter tests were performed. When we changed our outcome variable from years of schooling in 2014 to years of school in 2017, and the result is identical.. Bias-adj ATET coefficients are significantly negative around 0.5 (table 9). Education is a long-term effect and when parental migration happens at a time, it will disrupt the education of left-behind children and their school performance might continue to drop even after the return of the migrant parent. Thus, the result of education in 2017 might better reflect the consequence of past parental migration. Education outcome in 2014 might not be yet be affected immediately by recent parental migration.

Table 9: The effect on years of schooling in 2017 (children with absence of either parent)

n	m_eitherparent	control	Pseudo-R2	ATET	ATET bias-adj.
1	67	50	0.08539784	-0.0895522	-0.5757456

				(0.4740094)	(0.3684104)
2	67	87	0.04627136	-0.2164179	-0.5079593
				(0.400598)	(0.2850516)*
3	67	116	0.02309324	-0.2885572	-0.4882006
				(0.3853924)	(0.2724268)*
4	67	142	0.02391402	-0.358209	-0.5429163
				(0.3667271)	(0.2563743)**
5	67	166	0.03157118	-0.3283582	-0.5365705
				(0.3682481)	(0.2779717)*
6	67	188	0.03864217	-0.3656716	-0.5481321
				(0.3702523)	(0.2804416)*
7	67	210	0.03417707	-0.3006397	-0.5366594
				(0.3651637)	(0.2733788)*
8	67	226	0.03964204	-0.2947761	-0.4967879
				(0.3771774)	(0.278118)*
9	67	240	0.03445321	-0.2968491	-0.5193666
				(0.3805445)	(0.2846657)*
10	67	255	0.03508279	-0.3492537	-0.5587473
				(0.3826278)	(0.2804873)**

Notes: Standard errors are in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$; *n* represents the number of nearest neighbours used in the matching; the pseudo-R^2 is derived from the re-estimation of propensity score on the sample of matched children only.

Moreover, children education is only or mostly affected when parents migrated before children are too old. Education literature shows that the first years of education are the most important for learning. So, if parents were there before kids were a certain age example 12, their education is not affected by lack of parents' supervision after age 12. Thus, another robustness check was done by keeping in the sample only children who were younger than 12 when parents migrated. Table 10 report the same results where coefficients are significantly negative around 0.5.

Table 10: The effect on years of schooling in 2014 (children who were younger than 12 when parents migrated)

n	m_eitherparent	control	Pseudo-R2	ATET	ATET bias-adj.
1	107	81	0.0169186	-0.6095238	-0.5866826
				(0.3187056)*	(0.1820833)***
2	107	133	0.0166257	-0.4047619	-0.446051
				(0.2897111)	(0.1581487)***
3	107	183	0.0136392	-0.2888889	-0.4756735
				(0.2840083)	(0.1498119)***
4	107	228	0.0139601	-0.3619048	-0.4989524
				(0.2738137)	(0.1506466)***
5	107	267	0.0091156	-0.36	-0.4851567
				(0.2689028)	(0.149962)***
6	107	297	0.0065868	-0.368254	-0.4801351
				(0.2641906)	(0.1456012)***

7	107	321	0.0072857	-0.355102 (0.2606221)	-0.4482273 (0.1455732)***
8	107	345	0.0077225	-0.3130952 (0.2597462)	-0.440635 (0.1463983)***
9	107	367	0.0068772	-0.3142857 (0.2554029)	-0.4164871 (0.1461499)***
10	107	381	0.0070313	-0.2742857 (0.2563995)	-0.4047299 (0.1441897)***

Notes: Standard errors are in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$; *n* represents the number of nearest neighbours used in the matching; the pseudo-R^2 is derived from the re-estimation of propensity score on the sample of matched children only.

Falsification test

Since we tested our education outcome in 2014 and the phenomenon of migration occurred before or in 2014, it could be that there are unobservable factors that explain both education and migration. Thus, we did the falsification test using treatment in 2017. The idea is to do a placebo test; if a causal effect of migration exists, migration in 2017 should be orthogonal to education in 2014. But, if these un-observable factors exist, we should also find that migration in 2017 explains education in 2014. The treatment variable of this model is children with either parent being a migrant in 2017, and we restricted our sample to only control in 2014. If the results showed significantly different between control and treatment in this model, our logit model might not be correct. Table 11 shows no significant difference between the 2017 treatment, which supports our logit covariates. Thus, we can argue that the effect in our 2014 model is really a causal effect.

Table 11: The effect on years of schooling in 2014 (children with either parent absent) and 2017 treatment

n	m_eitherparent2017	control	Pseudo-R2	ATET	ATET bias-adj.
1	31	19	0.19260914	-0.6785714 (0.8180844)	-0.6888558 (0.8711313)
2	31	39	0.11005435	-0.1964286 (0.6818993)	-0.0741969 (0.2839212)
3	31	56	0.05431742	-0.0357143 (0.599791)	-0.0770727 (0.248067)
4	31	70	0.06938372	0.0267857 (0.5709233)	-0.1373899 (0.2665478)
5	31	82	0.06349063	0.1 (0.546867)	-0.1206856 (0.2558165)
6	31	91	0.05820419	0.0535714 (0.5430195)	-0.108851 (0.2504989)
7	31	100	0.0519658	0.1530612 (0.546624)	-0.098743 (0.2770165)
8	31	111	0.04004377	0.1428571	-0.0606714

				(0.5421282)	(0.2721687)
9	31	120	0.04267802	0.1825397	-0.0276896
				(0.5358221)	(0.2667789)
10	31	129	0.04275589	0.2357143	-0.0172371
				(0.5328821)	(0.2606876)

Notes: Standard errors are in parentheses; *** p < 0.01, ** p < 0.05, * p <0.10; n represents the number of nearest neighbours used in the matching; the pseudo-R^2 is derived from the re-estimation of propensity score on the sample of matched children only.

Table 12 and 13 report the results when we restrict our target children by age. Interestingly, a parent's migration only affects older children, meaning that the channel is not probably only the lack of parental care but also (mostly) the substitution effect (older children substitute parents at work). The migration of their parent translates into a larger burden in terms of work for older children then affecting their school performance. In table 14 and 15, we separate our sample by sex of children. The results show the same trend with the whole sample. However, the girl model is more significant and a little larger coefficient, suggesting parental migration has a more serious effect on girls rather than boys. Also, it would be interesting to look at the different effect of father's and mother's migration separately but we cannot because of fewer treated sample. Lastly, we dropped asset 2011 from the propensity score estimation model and the results were presented in table 16. We found similar results with asset included.

Table 12: The effect on Years of schooling in 2014 (12-19 years old children with absence of either parent)

n	m_eitherparent	control	Pseudo-R2	ATET	ATET bias-adj.
1	46	32	0.2330192	-1.577778	-0.9858437
				(0.5451337)***	(0.4782508)**
2	46	57	0.1364978	-1.022222	-0.8265597
				(0.4630066)**	(0.3696953)**
3	46	79	0.1126205	-0.9333333	-0.8297824
				(0.4456324)**	(0.3365622)**
4	46	99	0.0754315	-0.9888889	-0.7539741
				(0.4198076)**	(0.3351057)**
5	46	113	0.0522154	-1.106667	-1.03725
				(0.413323)***	(0.3084008)***
6	46	128	0.0492603	-1.040741	-0.8930175
				(0.413141)**	(0.3148739)***
7	46	143	0.0487219	-1.060317	-0.9401645
				(0.408347)***	(0.3204796)***
8	46	157	0.0470868	-1.094444	-0.9424039
				(0.4005164)***	(0.3133776)***
9	46	165	0.0375701	-1.079012	-0.9640823
				(0.4005824)***	(0.306788)***

10	46	175	0.033463	-1.086667	-1.009138
				(0.4013083)***	(0.3051111)***

Notes: Standard errors are in parentheses; *** *p* < 0.01, ** *p* < 0.05, * *p* <0.10; *n* represents the number of nearest neighbours used in the matching; the pseudo-R^2 is derived from the re-estimation of propensity score on the sample of matched children only.

Table 13: The effect on Years of schooling in 2014 (6-12 years old children with absence of either parent)

n	m_eitherparent	control	Pseudo-R2	ATET	ATET bias-adj.
1	86	62	0.07240897	0.1058824	-0.000559
				(0.2706556)	(0.2068642)
2	86	104	0.060239	0.1117647	-0.0583089
				(0.2431972)	(0.1777174)
3	86	140	0.04173567	0.1647059	-0.0043934
				(0.2278396)	(0.1610547)
4	86	168	0.02838054	0.1176471	-0.0468781
				(0.2289032)	(0.1570099)
5	86	194	0.02227826	0.1082353	-0.0606722
				(0.2251268)	(0.1493221)
6	86	213	0.02043262	0.0745098	-0.1061356
				(0.2238772)	(0.1444805)
7	86	235	0.01703704	0.0302521	-0.1371862
				(0.2206077)	(0.1412119)
8	86	254	0.01557989	0.05	-0.1200999
				(0.2196213)	(0.1405296)
9	86	273	0.0141935	0.0339869	-0.1356293
				(0.2195242)	(0.1410071)
10	86	290	0.01457056	-0.0047059	-0.1473183
				(0.2182998)	(0.1394241)

Notes: Standard errors are in parentheses; *** *p* < 0.01, ** *p* < 0.05, * *p* <0.10; *n* represents the number of nearest neighbours used in the matching; the pseudo-R^2 is derived from the re-estimation of propensity score on the sample of matched children only.

Table 14: The effect on Years of schooling in 2014 (Boys with absence of either parent)

n	m_eitherparent	control	Pseudo-R2	ATET	ATET bias-adj.
1	56	41	0.05202183	-0.3396226	-0.3751965
				(0.5391065)	(0.3616881)
2	56	72	0.02490279	-0.4811321	-0.5548052
				(0.4743704)	(0.2773656)**
3	56	98	0.02606553	-0.5471698	-0.6126824
				(0.460742)	(0.2668998)**
4	56	118	0.01328445	-0.4481132	-0.529489

				(0.4283847)	(0.2589305)**
5	56	140	0.01550052	-0.4377358	-0.5248104
				(0.400964)	(0.2446542)**
6	56	161	0.01257839	-0.4496855	-0.4820226
				(0.3928452)	(0.2372549)**
7	56	176	0.01254414	-0.5929919	-0.5227405
				(0.4073844)	(0.2459552)**
8	56	190	0.01036543	-0.6509434	-0.5667446
				(0.4049013)*	(0.2446605)**
9	56	205	0.01105277	-0.5660377	-0.5336384
				(0.4056494)	(0.2482698)**
10	56	214	0.01161326	-0.5528302	-0.531496
				(0.4004071)	(0.2451691)**

Notes: Standard errors are in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$; *n* represents the number of nearest neighbours used in the matching; the pseudo-R^2 is derived from the re-estimation of propensity score on the sample of matched children only.

Table 15: The effect on Years of schooling in 2014 (Girls with absence of either parent)

n	m_eitherparent	control	Pseudo-R2	ATET	ATET bias-adj.
1	63	44	0.07001936	0.047619	-0.6666155
				(0.5409007)	(0.2448945)***
2	63	76	0.03321529	0.047619	-0.5516621
				(0.4658365)	(0.2423814)**
3	63	99	0.03529312	-0.1111111	-0.6093446
				(0.4322483)	(0.2395252)**
4	63	118	0.02518259	-0.202381	-0.5893964
				(0.4305593)	(0.224209)***
5	63	138	0.02627397	-0.2412698	-0.5843846
				(0.4227079)	(0.2226816)***
6	63	154	0.02059231	-0.2910053	-0.550106
				(0.4139958)	(0.2151007)**
7	63	168	0.01709232	-0.3129252	-0.6050606
				(0.4178787)	(0.215896)***
8	63	184	0.01410686	-0.3551587	-0.6238848
				(0.4131854)	(0.2147757)***
9	63	199	0.01548453	-0.3068783	-0.5764753
				(0.4036519)	(0.2149186)***
10	63	213	0.01833591	-0.2777778	-0.5786339
				(0.401233)	(0.2167091)***

Notes: Standard errors are in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$; *n* represents the number of nearest neighbours used in the matching; the pseudo-R^2 is derived from the re-estimation of propensity score on the sample of matched children only.

Table 16: The effect on Years of schooling in 2014 (either parent migrant international or internal with no asset2011 in the estimation of the propensity score)

n	m_eitherparent	control	Pseudo-R2	ATET	ATET bias-adj.
1	126	90	0.0355988	-0.032	-0.5125445
				(0.3561975)	(0.2003303)**
2	126	164	0.0194099	-0.028	-0.3456095
				(0.3276316)	(0.1724974)**
3	126	216	0.0166099	-0.096	-0.372066
				(0.2995976)	(0.1618647)**
4	126	266	0.011696	-0.1508	-0.3544362
				(0.2867)	(0.1648013)**
5	126	311	0.0102814	-0.1344	-0.3957946
				(0.2785346)	(0.1581999)**
6	126	353	0.0093802	-0.1619048	-0.3668465
				(0.2731269)	(0.1570965)**
7	126	381	0.0094932	-0.1885714	-0.3747362
				(0.2679112)	(0.1567283)**
8	126	404	0.0078141	-0.23	-0.416697
				(0.2643741)	(0.1535891)***
9	126	429	0.0083387	-0.2568889	-0.3962492
				(0.2609944)	(0.1513052)***
10	126	453	0.0062621	-0.2888	-0.3772066
				(0.2578695)	(0.1506702)**

Notes: Standard errors are in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$; n represents the number of nearest neighbours used in the matching; the pseudo-R^2 is derived from the re-estimation of propensity score on the sample of matched children only.

6. Conclusion

This study is unlike previous studies into migration in Cambodia, by employing PSM to investigate the effect of parental migration on the educational outcomes of left-behind children in 11 rural villages in Cambodia. The first wave of data used from 2011 was used to construct pre-treatment covariates to satisfy the 'un-confoundedness assumption' which is the main assumption in PSM approaches. The second data wave in 2014 was used for the main analysis of the educational outcome and the third wave in 2017 was used for checking robustness and for falsification tests for treatment in 2017.

Our results indicate that parental migration has a significant negative effect on the children left behind. We find that the migration of at least one parent reduced the years of completed schooling of their children left at home by about half a year compared to children with both parents at home. The results also show the significantly little difference between the absence of parents due to migration, and absence due to other reasons. Children with migrant parents are fare a little better than those with otherwise absent parents, suggesting the possibility of the positive effect of remittances and/or the negative effect of parental absence due to other reasons besides migration. The migration of brothers or sisters of the children, while the parents are at home, has no effect on education. This can be explained by the fact that the parent is not absent. At the same time, we also see that there is not a positive effect of remittances on education. Or, if it exists, it is probably compensated by the child's work requirements for the family. Our results also show a similar pattern of impact on schooling outcomes for both boys and girls, with girls slightly more negatively affected than boys. Also, the falsification test provides proof that the effect in our 2014 model is really a causal effect.

Overall, our results strongly indicate that there is disruption of education of children left behind while at least one parent migrates. This clearly indicates that in the setting of the 11 rural villages tested, parental migration disrupts schooling and suggests a negative long-term implication of parental migration on livelihoods, and the welfare and economic development of these 11 rural communities if the trend continues. For this reason, especial educational programs for children affected by parental migration are needed, and ….

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ANNEX

Map of survey locations

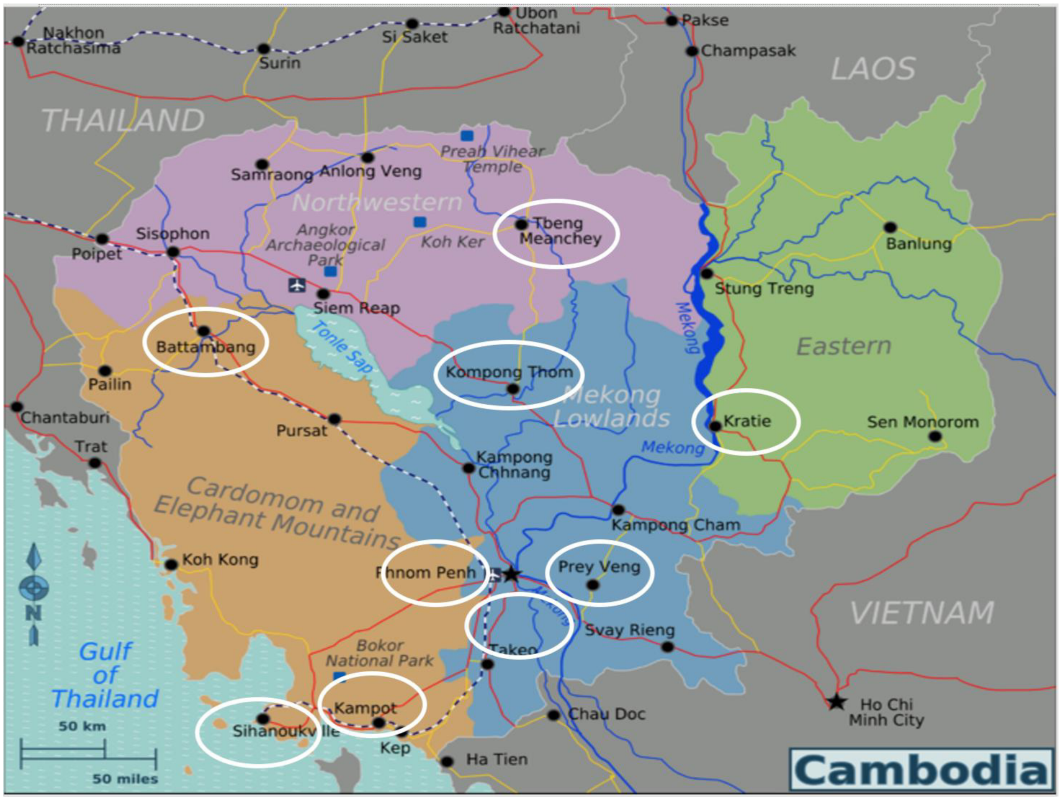

Table A1: B. In addition to the person living in your households, are there any other (spouse or son/daughter), 15 years and older, who previously has been a member of your household but hasn't appeared in this household after September 2013 (Pchum) or no longer living in this household?

No	Name (first names only)	Relation ship with hh head (codes below)	Sex 1=M 2=F	Age (year)	Marital status (codes below)	Education (Highest grade-number of year)	Where is [NAME] currently living? (code)	What year did [NAME] move to current location? (month/year)	Why did [NAME] move to current location (code)	What is [NAME] main occupation now? (code)	Have [NAME] send money home in the last 6 month? 1=Yes 2=No (ask the following member)	What is the total cost of the transfers and cash gifts that [NAME] has send to the household in the last 6 months? (moeun riels)	Through what means/channels do you/does your household receive the money? (code) (Primary means)
1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
20													
21													
22													
23													
24													
25													
26													
27													

Code IB: Question 3: 1= Household head, 2= Husband/wife, 3= Sister-/brother (in-law, sibling), 4= Son or daughter (adopted), 5= Son-/daughter-in-law, 6= Grandchild, 7= Stepchild, 8= Parent (in-law), 9= Grandparent, 10= Niece/Nephew, 11= other (specify)

Question 6: 1= Married, 2= Single, 3= Divorced, 4= Widow/Widower, 5= Deserted

Question 8: 1=Phnom Penh 2=other part of Cambodia 3=Thailand 4=Other countries (specify)

Question 10: 1=To take a job 2=To look for a job 3=To study 4=Other

Question 14: 1=Western Union 2=Bank transfer 3=From the person/by other person 4=Other (specify) 5=Wing

Table A2: Descriptive statistic of main variables comparing with national data (CSES)

Variable	**CSES 2014**	**CDRI 2014**
Household size	4.43	4.92
Female ratio	0.54	0.53
Working ratio	0.67	0.65
Dependency ratio	0.69	0.77
Education attainment of household member	**CSES 2014**	**CDRI 2014**
None or only some education	3.77	3.82
Primary school not completed	45.25	59.87
Upper Secondary not completed	46.11	32.01
Higher education	2.46	3.04
Vocational training	2.38	0.39
Others	0	0.05
Don't know	0.03	0.81
Population by age	**CSES 2014**	**CDRI 2014**
1-14 years old	30.31	31.66
15-64 years old	64.22	61.53
65-max years old	5.48	6.82

Note: CSES: Cambodian Social Economic Survey

Table A3: Descriptive statistic of main variables comparing with missing households

Variable	**CDRI 2011 (n=91)**	**CDRI 2011 (n=1123)**
Household size	5.30	5.62
Female ratio	0.54	0.52
Working ratio	0.63	0.65
Dependency ratio	0.87	0.77
Asset	16.43	24.31
Education attainment of household member	**CDRI 2011 (n=91)**	**CDRI 2011 (n=1123)**
None or only some education	17.27	19.66
Primary school not completed	51.58	47.63
Upper Secondary not completed	28.95	28.97

Higher education	0.73	3.25
Don't know	1.46	0.49
Population by age	**CDRI 2011 (n=91)**	**CDRI 2011 (n=1123)**
1-14 years old	33.82	31.58
15-64 years old	60.58	63.17
65-max years old	5.6	5.25

Table A4: Estimation of the propensity score, logit model

Dependent variables	**Migration either parents**	**Migration either parents with no assets**
Asset2011	-0.0165389	None
	(0.0092212)*	
HH Size	-0.2271615	-0.142843
	(0.1364431)*	(0.1326853)
Number of working	0.3280758	0.1906517
	(0.2392946)	(0.2325144)
Dependency ratio	0.0940287	0.0024328
	(0.2711491)	(0.2746043)
Share of working female	-1.18959	-1.089378
	(0.6158262)*	(0.6010487)*
Age of Mother	0.0085584	0.0088894
	(0.0241199)	(0.0233696)
Mother's education	-0.0829287	-0.0843518
	(0.0467865)*	(0.0454777)*
Age of father	-0.1660183	-0.1702871
	(0.0231783)***	(0.022686)***
Father's education	0.1190444	0.0743564
	(0.0404353)***	(0.0370928)**
Sex	0.0428644	-0.0706773
	(0.2375566)	(0.2283347)
Age	-0.016177	-0.0160125

	(0.0352244)	(0.0340667)
Village 1	0.8985093	0.4978192
	(0.4343649)**	(0.4029027)
Village 2	0.4846237	0.1240495
	(0.4538011)	(0.439048)
Village 3	0	-3.32037
	(omitted)	(1.063681)***
Village 4	-0.3417986	-0.6945592
	(0.5080251)	(0.4891225)
Village 5	-1.15637	-1.299021
	(0.5310365)**	(0.5248807)**
Village 6	-0.0192397	-0.0228297
	(0.474333)	(0.4667038)
Village 7	-0.8144263	-1.086371
	(0.4918506)*	(0.4734324)**
Village 8	-0.3698386	-0.6332642
	(0.5565814)	(0.5391457)
Village 9	0	0
	(omitted)	(omitted)
Village 10	-0.0934307	-0.1355449
	(0.5314249)	(0.4352617)
Village 11	0	0
	(omitted)	(omitted)
_cons	4.849632	5.031582
	(0.9715282)***	(0.953061)***
Pseudo R2	0.2819	0.2809
Observation	1,534	1,738

Notes: Standard errors in parenthesis; ***p < 0.01, **p < 0.05, *p < 0.1; in specification 2, asset 2011 was dropped from the model.

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