Learning Levels of Children from Short-Term Migrant Families: Evidence from Rural India

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Abstract

What happens to the learning levels of children from short-term migrant families in rural India? We explore this question using India Human Development Survey 2011-12. Results indicate that children from migrant families have lower language and mathematics levels than children from non-migrant families. Estimates remain robust to instrumental variable approach. Next, we use unique primary data collected from Odisha in 2019 and examine if left-behind children can retain their learning levels. We find that percentile rank of language and mathematics of left-behind children were not different from that of children from non-migrant families. Percentile rank of migrant children were lower.

Keywords— *learning levels, short-term migration, rural India, government policy*

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1 Introduction

At the global level, access to primary education has seen a significant improvement in the last few decades. However, an increase in access to education has not translated into an improvement in quality of education. Over 250 million children do not have the basic proficiency in literacy and numeracy skills, let alone more refined skills that are required to get decent work (UNESCO, 2013). This remains a point of concern since learning outcomes play a major role in shaping individual's earning potential and quality of life (Hanushek & Woessmann, 2008; Lazear, 2003; Stiglitz et al., 2009).

An inspection into the group of children who fall behind shows that the children from internal migrant families tend to fall behind in terms of acquiring appropriate learning levels. Children from migrant families have lower test scores than children from non-migrant families in China (Zhang et al., 2014; Zhao et al., 2014). In India too, Nguyen (2016) provides evidence that children from short-term migrant families in the state of Andhra Pradesh have lower cognitive ability relative to children from non-migrant families. There is, however, a paucity of research that has determined this relation at the national level in India. We propose to address this gap in the present study.

We start by assessing the variation in learning levels of children from short-term migrant families in rural India. We examine this for children aged 8-11 years using India Human Development Survey (IHDS)-II data, 2011-12. We find that children from short-term migrant families have acquired lower age-appropriate skills in reading and mathematics, relative to children from non-migrant families. As a robustness check we instrument the presence of a short-term migrant member in the household with the lagged rate of short-term migrants in district using National Sample Survey Organisation's (NSSO) Employment & Unemployment and Migration Particulars Survey 2007-08 and proportion of workers involved in manufacturing industries in other districts of the state from NSSO's Employment and Unemployment Survey 2009-10. Additionally, we test for omitted variable bias using methodology developed by Oster (2019). Our results remain robust to these tests.

The challenges faced by these children has not gone unrecognised by the Indian policymakers. The Right to Education (RTE) Act of 2009 addresses the challenges faced by children from short-term migrant families. Based on RTE, one of the strategies laid out by Sarva Shiksha Abhiyan 2011 is operating seasonal hostels in high out-migration prone villages to protect children's right to education (GOI, 2011). The state government of Odisha has adopted this strategy. The government operationalizes seasonal hostels in high out-migration prone villages of the state. In this context, we examine whether seasonal hostels can help these children to retain their test scores. The result suggests that children who had out-migrated with their family members have lower percentile rank in both language and mathematics. However, percentile rank of left-behind children in hostels, or otherwise, were not significantly different from that of children from non-migrant families. If we only consider children from migrant families, left-behind children in seasonal hostels have the highest percentile rank. Thus, operating hostels and encouraging migrant families to leave their children behind is a way of protecting child's right to education. This study contributes to the literature in two ways. First, we provide a causal link between migration of family members and learning levels of children using a large scale household survey in India. Second, we assess whether leaving children behind in seasonal hostels can help them mitigate these challenges.

The paper is structured as follows. In section 2 we present the background of the study. In section 3 we examine the link between short-term migration of family members and learning levels of children using IHDS-II data. In section 4 we extend the hypothesis to primary survey data. Section 5 concludes.

2 Background

The challenges faced by children from short-term migrant families can be manifold. The duration of short-term migration overlaps with the school academic calendar (Smita, 2008; Srivastava Ravi & Dasgupta, 2010). Hence, children who out-migrate with their parents can be nominally enrolled in the register but they miss out on a considerable part of the academic year. On the other hand, left-behind children can be irregular in attending school due to lack of parental guidance. The disruption in schooling could affect their learning levels. If this negative effect is commonly faced by children in high out-migration prone districts, then it is reasonable to assume that it would get reflected in the nationally representative data as well. We look at the literacy and numeracy levels of children from Annual Status of Education Report (ASER)[1] of 2018 to examine this conjecture. As an example we consider the state of Odisha where 11 districts have been identified as major source districts of distress-driven out-migration by the Labour Department of Odisha. It has been further highlighted in the

[1]ASER is a nationally representative survey that collects information about learning outcomes of children, details of household and characteristics of schools in rural India. During household surveys children are asked to perform a short test on language and mathematics and their levels are determined based on their performance. ASER is representative at the district level.

Table 1: Learning levels of children in selected districts of rural Odisha in 2018

Districts	Percentage of children		
	Aged 6-14 years who are out of school	In grades 3-5 who can read standard 2 text	In grades 3-5 who can do at least subtraction
Balangir	0.3	30.2	21.4
Bargarh	0.0	60.2	38.6
Gajapati	1.9	33.6	34.4
Ganjam	2.0	68.9	58.0
Kalahandi	1.5	42.0	32.8
Koraput	7.4	19.5	12.7
Malkangiri	7.1	14.0	16.4
Nabarangpur	5.7	21.2	15.4
Nuapada	2.0	18.1	17.6
Rayagada	7.8	15.8	8.5
Subarnapur	0.3	48.7	41.6
Odisha	1.5	49.0	40.7

Source: ASER Report, 2018

Report of the Working Group on Migration (GOI, 2017)[2].

The results are presented in Table 1. We find that in nine out of the eleven districts, percentage of children in grades 3-5 who could read a standard 2 text was lower than the state average. The performance of children in mathematics was even worse. This provides suggestive evidence that children from migrant households could have lower learning levels. We examine this linkage at the national level.

3 Evidence from a Large Scale Survey of Households

3.1 Data

We examine the linkage between short-term migration of household members and learning levels of children using data from IHDS-II survey conducted by National Council of Applied Economic Research and University of Maryland in 2011-12. IHDS-II comprises of 42,152 households (27,579 in the rural sector and 14,573 in the urban sector), spread over 384 districts in 1420 villages and 1042 urban blocks. It is a nationally representative data source which collects information on several components including individual and household details, medical and school facilities, details of village and migration history of household members among the others. Additionally, it collects information about learning levels of children.

[2]The 11 districts which are identified as high seasonal out-migration prone are Balangir, Bargarh, Gajapati, Ganjam, Kalahandi, Koraput, Malkangiri, Nabarangapur, Nuapada, Rayagada and Subarnapur

The survey collected information on mathematics and language levels of children aged 8–11 years in the household. Every child was asked to read, write and solve mathematical problem in a language that the child was comfortable in[3]. A child's reading level was assigned as follows: a value of 0 if the child could not read, 1 if the child could identify letters, 2 if child could read a word, 3 for paragraph and 4 for story. Similarly, for assessing mathematical skill, a value of 0 was assigned if the child could not recognize numbers, 1 if child could identify numbers, 2 if child could solve subtraction problem and 3 if the child could solve a division problem.

We compare these learning levels with the parameters set by the National Council of Educational Research and Training (NCERT), Government of India. NCERT defines the minimum skills that need to be achieved by the children in India, based on their age (NCERT, 2005, 2017). We refer to it age-appropriate skill for the rest of the chapter. We generate the first outcome variable 'read' for reading levels that take the value 1 if a child has acquired the age-appropriate skills in reading and 0 otherwise. The variable 'read' takes the value 1 if: an 8-year-old child can read words, 9-year-old can read a sentence and a 10-11-year-old child can read a story. Otherwise the variable takes the value 0. Similarly, we define a variable 'math' to test a child's numerical skills. The variable takes the value 1 if an 8-year-old child can recognize numbers below 99 and 9-11-year-old children are able to perform division. Otherwise the variable takes the value 0[4]. We examine the variation in learning levels of children based on the presence of a short-term migrant (STM) member in the family. We define a short-term migrant as a person who had migrated for more than one month but less than six months in the year preceding the survey. A family which has at least one migrant member is considered to be a migrant family.

In Table 2 we provide the descriptive statistics. We find that children aged 8-11 years from non-migrant families had higher mathematics as well as reading skills relative to children from short-term migrant families. An equality of proportion test suggests that the difference between the two groups was significantly different from zero for both reading and mathematics skill. The households with short-term migrant have lower resources as evident from their monthly per capita consumption expenditure (MPCE). Migrant households were mainly engaged as wage labourer in agricultural or non-agricultural activities. Migrant families have a higher share of illiterate households as compared to non-migrant families.

[3]The survey tool was developed and pretested by the survey team in several languages to ensure comparability

[4]Similar variable was created by Chatterjee et al. (2018)

Table 2: Descriptive statistics: learning levels for children aged 8-11 years in rural sector from IHDS-II data

	No STM in family	STM in family
Proportion of children who have acquired age-appropriate math skills	0.32	0.20
Proportion of children who have acquired age-appropriate reading skills	0.52	0.39
Proportion of male children	0.52	0.51
Proportion of female children	0.48	0.49
Age of child (average)	9.49	9.47
Number of household members	6.52	7.06
MPCE (in rupees)	1434	1057
Log of MPCE	7.08	6.82
Religion: Proportion Hindu	0.81	0.85
Religion: Proportion Muslim	0.13	0.14
Religion: Proportion Others	0.06	0.01
Proportion: Type of household		
Cultivation/ allied	0.37	0.41
Agricultural wage labour	0.13	0.15
Non-agricultural wage labour	0.25	0.38
Organised/ business/ salaried	0.11	0.02
Others	0.14	0.05
Social Group: Proportion of ST	0.11	0.17
Social Group: Proportion of SC	0.23	0.24
Social Group: Proportion of OBC	0.41	0.47
Social Group: Proportion Others	0.25	0.12
Proportion of male household head	0.88	0.93
Proportion of female household head	0.12	0.07
Average age of household head	46	45
Education of household head		
Proportion illiterate	0.70	0.81
Proportion completed below primary	0.10	0.07
Proportion completed primary	0.07	0.06
Proportion completed middle school or above	0.13	0.06
Source: IHDS-II, 2011-12		

3.2 Method

There are two outcome variables in our study: age-appropriate learning levels in reading and mathematics. The main explanatory variable is the presence of short-term migrant member in the family. Other covariates are child's age and gender, religion, social group of the household, educational attainment, gender and age of the household head. There is evidence in the literature showing children from Scheduled Tribe (ST) and Scheduled Caste (SC) households perform worse than the children from other social groups. We include a dummy with base as ST. The education level of household head could determine child's learning level. We include a variable for education of household head, with the base: illiterate. The other household level controls considered are number of members in the household, log of monthly per capita consumption expenditure of the household, as the proxy for household income as well as the main occupation of household. We also control for state fixed effects.

More formally, for each child 'i' residing in household 'h' in district 'd' and state 's', we examine the variation in the variables 'read' and 'math' based on whether the child belongs to a short-term migrant household (STM=1) or not (STM=0), controlling for other individual ($Child_{ihds}$), household characteristics (HH_{hds}) and state fixed effects γ_s. More specifically we estimate

$$Y_{ihds} = \alpha + \beta_1 STM_{hds} + \beta_2 HH_{hds} + \beta_3 Child_{ihds} + \gamma_s + \epsilon_{ihds} \quad (1)$$

The variable of interest is STM_{hds} and the coefficient of interest is 'β_1'. If children from migrant families face disadvantages and have lower age-appropriate learning levels, then we would expect 'β_1' to be negative.

A key concern in the current specification is that the decision to out-migrate for a short term could be endogenous to child's learning levels. There are unobserved factors like labour market shock, health concerns of household members that can simultaneously affect child's learning level and household's migration decision (Zhang et al., 2014; Zhao et al., 2014). Therefore we adopt an instrumental variable estimation strategy to address the potential endogeneity concerns of short-term migration of household member and learning levels of children from these families.

We use two variables, both lagged proportions at the district level, as instrument for STM. The first is the rate of short-term migration in the district. That is, for every district we calculate the share of STM out of workers aged 15-65 years. It is obtained from NSSO's Employment & Unemployment and Migration Particulars Survey 2007-08. Stronger migrant network exists in districts that experience a higher rate of migration in the past. This could affect the flow of current migration in the district. Lagged rate of migration has been commonly used in the literature to instrument present migration decision (Binzel & Assaad, 2011; Chandrasekhar et al., 2017; Lokshin & Glinskaya, 2009; Mendola & Carletto, 2012).

The second instrument that we use is the share of individuals working in the manufacturing industry in the other districts of the state. In other words, for each district we calculate the share of workers working in manufacturing sector in all other districts of the state. This is calculated from NSSO's Employment and Unemployment Survey 2009-10. NSSO Employment & Unemployment and Migration Particulars round 2007-08 suggests that manufacturing sector is the third largest sector absorbing short-term migrants in India, after construction sector and agricultural sector (Srivastava, 2011). This variable would capture the extent of work available in other districts which is likely to increase rate of short-term migration from the present district. We argue that lagged district proportion will increase short-term migration of adults, but it is unlikely to affect the learning levels of children from these families. We control for nightlights in the district in the year 2011 to account for the economic prosperity of the region. Thus the first stage equation giving us the estimate for short-term migrant in the household is

$$STM_{hds} = \alpha + \mu X_{ihds} + \gamma C_{hds} + \delta Z_{ds} + \epsilon_{hds} \tag{2}$$

where C_{hds} is a set of exogenous variables that affect short-term migration decision of household 'h' in district 'd' of state 's'. Z_{ds} is a set of instruments which are highly correlated with short-term migration decision of household members but not with the error term ϵ_{hds}. The second stage regression would be given by

$$Y_{ihds} = \delta + \beta_1 X_{ihds} + \beta_2 HH_{hds} + \delta STM_{hds} + \gamma_s + \epsilon_{ihds} \tag{3}$$

where Y_{ihds} denotes the outcome variable – child 'i' from household 'h' in district 'd' and state 's' has acquired age-appropriate skills in mathematics or not or child has acquired age-appropriate skills in reading or not. X_{ihds} denotes individual control and HH_{hds} denotes the set of individual controls that are specified before. The primary variable of interest is denoted by STM_{hds}.

Although IHDS-II captures information on learning levels of children that could be modeled as ordered probit, we consider binary dependent variables mainly for two reasons. First, there are econometric issues in using instrumental variable to tackle endogeneity in ordered probit model framework especially when the explanatory variable is binary (Chandrasekhar et al., 2017). Second, it is preferable to estimate a linear model when the primary interest is to obtain marginal effects of the explanatory variable (Angrist, 2001; Angrist & Pischke, 2009).

3.3 Result

The baseline results are presented in Table 3. The estimates suggest that relative to children from non-migrant families, children from short-term migrant families had lower age-appropriate learning levels in mathematics and language[5].

The results from other covariates suggest that children from resource-rich households have higher learning levels relative to children from resource-poor households. Compared to children belonging to Hindu families, children from Muslim families had lower age-appropriate learning levels in both mathematics and reading. Children belonging to families engaged as wage labour have lower learning levels than children from families involved in cultivation and allied activities. The children in households with more educated head perform better than households with illiterate household heads. This could result from the added inputs and guidance of the literate household heads. We assess the validity of these results using a set of robustness checks.

[5]We perform a similar exercise to examine what happens to the learning levels of children when their parents out-migrate. Since multiple married couples and children in joint families make identification of parents difficult, we could only keep families where the parent of the child could be precisely identified. The baseline results suggest that out-migration of parents have a negative effect on learning levels of children (Appendix Table A1)

Table 3: Odds ratio from logit regression and coefficients from linear probability model representing learning levels of children by short-term migration status of family members

	Mathematics		Reading	
	Logit	LPM	Logit	LPM
Child is from non-migrant hh				
Child is from migrant hh	0.693***	-0.055***	0.751**	-0.063***
	(0.096)	(0.021)	(0.086)	(0.024)
Age of child	0.438***	-0.150***	0.756***	-0.062***
	(0.013)	(0.005)	(0.017)	(0.005)
Female child	0.818***	-0.036***	0.960	-0.009
	(0.043)	(0.009)	(0.046)	(0.011)
Household size	0.986	-0.002	0.987	-0.003
	(0.012)	(0.002)	(0.011)	(0.002)
Log MPCE	1.561***	0.080***	1.628***	0.108***
	(0.091)	(0.010)	(0.085)	(0.011)
Religion (Hindu)				
Muslim	0.604***	-0.087***	0.542***	-0.138***
	(0.059)	(0.016)	(0.046)	(0.018)
Others	0.950	-0.008	1.165	0.033
	(0.166)	(0.032)	(0.185)	(0.034)
Type of HH (Cultivation/ allied)				
Agri. wage labour	0.905	-0.017	0.850*	-0.038**
	(0.082)	(0.016)	(0.071)	(0.018)
Non-agri. wage labour	0.835**	-0.029**	0.798***	-0.051***
	(0.064)	(0.013)	(0.053)	(0.015)
Organised/ business/ salaried	1.380***	0.062***	1.432***	0.079***
	(0.130)	(0.018)	(0.123)	(0.019)
Others	1.236**	0.041***	1.188**	0.038**
	(0.106)	(0.016)	(0.092)	(0.017)
Social Group (ST)				
SC	1.297**	0.040**	1.238**	0.049**
	(0.139)	(0.017)	(0.120)	(0.021)
OBC	1.414***	0.056***	1.794***	0.133***
	(0.142)	(0.016)	(0.163)	(0.020)
Others	1.461***	0.063***	1.817***	0.136***
	(0.166)	(0.019)	(0.187)	(0.022)
Female head of household	0.935	-0.012	0.917	-0.020
	(0.081)	(0.015)	(0.071)	(0.017)
Age of household head	1.007***	0.001***	1.007***	0.002***
	(0.002)	(0.000)	(0.002)	(0.000)
Education of head (Illiterate)				
Below primary	1.108	0.016	1.309***	0.062***
	(0.102)	(0.016)	(0.106)	(0.019)
Primary	1.036	0.008	1.188*	0.038*
	(0.108)	(0.019)	(0.113)	(0.021)
Middle or above	1.498***	0.077***	1.486***	0.088***
	(0.127)	(0.016)	(0.114)	(0.017)
Constant	21.219***	1.055***	0.111***	0.010
	(12.182)	(0.103)	(0.056)	(0.111)

Table 3 Continued				
	Logit	LPM	Logit	LPM
State Fixed Effects	Yes	Yes	Yes	Yes
Observations	8,052	8,054	8,087	8,089
R-squared		0.181		0.109

Source: Author's calculation from IHDS-II data. Robust errors are presented in parenthesis. Level of significance *** <1%, ** <5 % and *<10%

3.4 Robustness Check

3.4.1 Assessing Omitted Variable Bias

We control for a large number of variables that could potentially affect learning levels of children. Even then, there could be unobserved variables that affect short-term migration decision as well as learning levels of children. Thus omitted variable bias could pose as a threat to our estimates. To overcome this, we use the method proposed by Oster (2019) that suggests that the extent of potential omitted variable bias in estimate can be calculated by estimating bias-adjusted β and R_{max}. We consider $R_{max} = \min\{1.3R^2,1\}$, where R^2 is obtained from regression with full set of control variables (Oster, 2019). We present the results in Table 4. We observe that bias adjusted β is negative and falls within the confidence interval of the baseline estimate. In the last column we estimate δ for which the value of β will be zero.

We find that impact of omitted variables on mathematics levels would have to be 3.2 times the impact of observable factors in order for the effect of short-term migration to be zero. Similarly, the impact of omitted variables have to be 4.8 times the influence of observable factors on reading levels for the effect to be zero. This is less likely to hold since we have controlled for a set of variables.

3.4.2 Instrumental Variable Approach

As a further robustness check, we adopt an instrumental variable approach. The first-stage results are presented in Table 5. We find that lagged rate of short-term migration in a district has a positive and significant effect on current migration decision of households. We also find that share of workers in manufacturing industry in other districts has a positive and significant effect on current migration decision. This asserts our earlier expectation that current migration would be higher in regions that have an existing network.

Table 4: Assessment of potential bias due to unobserved factors

	Coefficient of presence of short-term migrant member in family			
	Uncontrolled (R_2)	Controlled (R_2)	Identified (Estimated bias)	
			β for δ = 1 or -1	δ for β =0
	(1)	(2)	(3)	(4)
Mathematics	-0.116	-0.061	[-0.079, -0.043]	3.25
	(0.003)	(0.176)	(0.00033)	
Reading	-0.126	-0.07	[-0.084, -0.056]	4.78
	(0.003)	(0.106)	(0.00019)	

Source: Author's calculation. Uncontrolled coefficient is obtained from the regression of learning levels on presence of short-term migrant member in family without any other covariate. Controlled coefficient includes all covariates. The result is obtained using the command 'psacalc' in Stata following Oster (2019).

Among household types we notice that households involved in non-agricultural wage labour are more likely to out-migrate. Households who are engaged in business or have salaried income are better off financially. Thus, they are less likely to out-migrate for a short term. Among the social groups we find that ST households are more likely to out-migrate. This is in line with the literature which states that migrants are more likely to be from backward classes (Srivastava, 2011).

Table 5: First stage regression results: IHDS-II

Variables	LPM		IV-Probit	
	(1)	(2)	(3)	(4)
	Math	Read	Math	Read
Proportion of short-term migrants in district in 2007-08	0.308***	0.307***	0.307***	0.307***
	(0.067)	(0.067)	(0.067)	(0.067)
Proportion of manufacturing workers in other districts of state in 2009-10	0.861**	0.863**	0.968**	0.781**
	(0.427)	(0.427)	(0.384)	(0.388)
Age of child	0.0001	0.001	0.0001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Child is female	-0.005	-0.004	-0.005	-0.004
	(0.005)	(0.005)	(0.005)	(0.005)
Number of household members	0.003*	0.003*	0.003*	0.003*
	(0.001)	(0.001)	(0.001)	(0.001)
log MPCE	-0.008	-0.008	-0.008	-0.008
	(0.006)	(0.006)	(0.006)	(0.006)
Religion (Hindu)				
Muslim	0.010	0.010	0.010	0.010
	(0.010)	(0.010)	(0.010)	(0.010)
Others	-0.013	-0.014	-0.013	-0.014
	(0.009)	(0.009)	(0.009)	(0.009)
Type of household (cultivation/ allied)				

Table 5 Continued				
	Math	Read	Math	Read
Agricultural wage labour	0.013	0.013	0.013	0.013
	(0.011)	(0.011)	(0.011)	(0.011)
Non-agricultural wage labour	0.022**	0.022**	0.022**	0.022**
	(0.009)	(0.009)	(0.009)	(0.009)
Organised/ business/ salaried	-0.023***	-0.023***	-0.023***	-0.023***
	(0.007)	(0.007)	(0.007)	(0.007)
Others	-0.025***	-0.025***	-0.025***	-0.025***
	(0.007)	(0.007)	(0.007)	(0.007)
Social Group (ST)				
SC	-0.025*	-0.025*	-0.025*	-0.025*
	(0.014)	(0.014)	(0.014)	(0.014)
OBC	-0.022*	-0.021*	-0.022*	-0.021*
	(0.013)	(0.013)	(0.013)	(0.013)
Others	-0.036***	-0.036***	-0.036***	-0.036***
	(0.013)	(0.013)	(0.013)	(0.013)
Female head of household	-0.018**	-0.018**	-0.018**	-0.018**
	(0.008)	(0.008)	(0.008)	(0.008)
Age of household head	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Eduaction of head (Illiterate)				
Below primary	-0.015*	-0.016*	-0.015*	-0.016*
	(0.008)	(0.008)	(0.008)	(0.008)
Primary	-0.012	-0.012	-0.012	-0.012
	(0.010)	(0.010)	(0.010)	(0.010)
Middle or above	-0.010	-0.010	-0.010	-0.010
	(0.008)	(0.008)	(0.008)	(0.008)
Constant	-0.001	-0.001	-0.015	0.010
	(0.073)	(0.073)	(0.071)	(0.072)
Athro			0.851***	0.815***
			(0.210)	(0.202)
lnsigma			-1.538***	-1.539***
			(0.026)	(0.026)
Observations	7,803	7,837	7,803	7,837

Source: Author's calculation from IHDS-II data of 2011-12. Instruments are constructed from NSSO's Employment & Unemployment and Migration Particulars 2007-08 and NSSO's Employment & Unemployment Survey 2009-10. Nightlights in district is controlled. Standard errors clustered at the household level are given in the parenthesis. Level of significance ***<1% **<5% and *<10%

The results of validity of instruments and the associated tests are reported in Table 6. We notice that the F statistic is greater than the desired value of 10 (Staiger & Stock, 1994). Results from Kleibergen-Papp rk Lagrange multiplier strongly rejects the null hypothesis of under-identification. The Cragg-Donald statistic exceeds the critical value under Stock-Yogo at 10 percent significance level, indicating that estimator is not weakly identified. The high p-value obtained from Sargan-Hanson J-test suggests that the instruments are valid. Finally, we check for the endogeneity of the STM. The null hypothesis is that the regressor deemed to be endogenous is actually exogenous. We find that the hypothesis is rejected for both at one per cent level. Thus, it is right for us to treat migration decision as endogenous to learning levels in the study.

Table 6: Validity of the instruments

	Mathematics	Reading
First-stage F test of excluded instrument	11.78	11.80
Probability >F	(0.00)	(0.00)
Under-identification test		
Kleibergen-Paap rank LM statistic	24.02	24.05
	(0.00)	(0.00)
Weak identification test		
Cragg-Donald Wald F statistic	25.34	23.32
Stock-Yogo weak ID test critical values for single endogenous regressor		
10 % maximal IV size	19.93	19.93
15 % maximal size	11.59	11.59
Over-identification test (Hansen J statistic)	0.108	0.079
	(0.74)	(0.78)
Endogeneity test	22.46	22.44
	(0.00)	(0.00)

Source: The estimates are obtained using 'ivreg2' command of Stata. Both the instruments are taken into account. Standard errors are clustered at the household level

Results from second stage regressions are presented in Table 7. We find that short-term migration of household member negatively affects child's learning levels. In other words, at each age, children from migrant households have a lower chance of acquiring age-appropriate skills in reading and mathematics than children from non-migrant households. Household characteristics show that children from richer households perform better in terms of achieving age-appropriate skills. Children from SC and ST households perform worse than those from other social groups. In terms of household head's educational attainment, we find that households have a positive effect on child's education only when their educational attainment is at least till middle school.

Overall, the results suggest that the presence of short-term migrant in household negatively affects child's learning outcomes. The results hold true even after accounting for endogeneity concerns in the model.

Table 7: Second stage regression results: IHDS-II

Variables	LPM		IV-Probit	
	(1)	(2)	(3)	(4)
	Math	Read	Math	Read
Child is from migrant hh	-1.306***	-1.589***	-3.342***	-3.239***
	(0.373)	(0.459)	(0.498)	(0.511)
Age of child	-0.149***	-0.060***	-0.336***	-0.122***
	(0.005)	(0.006)	(0.051)	(0.021)
Child is female	-0.041***	-0.016	-0.102***	-0.032
	(0.011)	(0.013)	(0.030)	(0.027)
Number of hh members	0.001	0.002	0.003	0.003
	(0.003)	(0.003)	(0.007)	(0.007)
log MPCE	0.069***	0.095***	0.161***	0.193***
	(0.013)	(0.015)	(0.045)	(0.047)
Religion (Hindu)				
Muslim	-0.073***	-0.128***	-0.175***	-0.258***
	(0.021)	(0.025)	(0.064)	(0.067)
Others	-0.028	-0.005	-0.066	-0.011
	(0.034)	(0.038)	(0.078)	(0.079)
Type of household (cultivation/ allied)				
Agricultural wage labour	-0.008	-0.021	-0.022	-0.039
	(0.021)	(0.027)	(0.055)	(0.056)
Non-agri. wage labour	-0.003	-0.015	-0.007	-0.028
	(0.019)	(0.023)	(0.050)	(0.050)
Organised/ business/ salaried	0.033	0.048*	0.055	0.102*
	(0.023)	(0.025)	(0.057)	(0.060)
Others	0.005	-0.003	-0.001	-0.007
	(0.021)	(0.024)	(0.051)	(0.049)
Social Group (ST)				
SC	0.010	0.017	0.046	0.031
	(0.027)	(0.033)	(0.073)	(0.069)
OBC	0.027	0.105***	0.088	0.209***
	(0.025)	(0.031)	(0.070)	(0.077)
Others	0.016	0.090***	0.056	0.176**
	(0.029)	(0.035)	(0.078)	(0.085)
Female head of hh	-0.039**	-0.050**	-0.098**	-0.104**
	(0.019)	(0.023)	(0.045)	(0.045)
Age of household head	0.001	0.001	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Eduaction of head (Illiterate)				
Below primary	-0.006	0.040	-0.018	0.079
	(0.021)	(0.025)	(0.051)	(0.054)
Primary	-0.013	0.017	-0.041	0.038
	(0.023)	(0.028)	(0.054)	(0.058)
Middle or above	0.063***	0.069***	0.138**	0.141***
	(0.020)	(0.022)	(0.055)	(0.053)
Constant	1.250***	0.225	1.676***	-0.556
	(0.134)	(0.156)	(0.317)	(0.358)

Table 7 Continued				
	Math	Read	Math	Read
Observations	7,803	7,837	7,803	7,837

Source: Author's calculation from IHDS-II data of 2011-12. Instruments are constructed from NSSO's Employment & Unemployment and Migration Particulars 2007-08 and NSSO's Employment & Unemployment Survey 2009-10. Nightlights in district is controlled. Standard errors clustered at household level are given in parenthesis. Level of significance ***<1%, **<5% and *<10%

The challenges faced by children from short-term migrant families have been recognised by the policymakers in India and the Right to Education (RTE) Act, 2009 addresses them. RTE Act makes local government responsible to ensure admission of children from migrant families. Based on that, the Sarva Shiksha Abhiyan Framework for Implementation of RTE Act, 2011 suggests various strategies to protect right to education of children from migrant families (GOI, 2011, p. 39). While operating seasonal hostels in the source villages can retain children in the source villages, strategies like operating work-site schools, issuing migration cards, arranging for transportation in the destination areas can protect right to education of migrant children. The implementation of these strategies, however, has varied across states of India. Among the others, the Government of Odisha operates seasonal hostels in the out-migration prone villages[6] and encourages parents to leave their children behind in source villages when they out-migrate[7]. In this context we we examine whether leaving children behind in the source villages can be an effective way of mitigating the challenges faced by them. More specifically, we examine the variation in learning outcomes of children by their living arrangement when their household members out-migrate using a unique survey data collected from Nuapada district of Odisha in 2019.

4 Evidence from Primary Survey

4.1 Data

We examine the efficacy of seasonal hostels using data collected from Nuapada district of Odisha in July-August, 2019. Nuapada district forms a part of the backward Kalahandi Balangir Koraput (commonly known as KBK) region of Odisha. Short-term migration is distress driven in this region since most of the area is single cropped and has very low irrigation facilities (Srivastava Ravi & Dasgupta, 2010). Nuapada is identified by the Labour

[6] https://seshagun.gov.in/sites/default/files/2019-05/Odisha24973.pdf
[7] http://opepa.odisha.gov.in/website/Download/28-30-07-2014_Local_Authority.pdf

Department as one of the out-migration prone districts of Odisha. The School and Mass Education Department operates seasonal hostels in high out-migration prone villages of this district to retain children from migrant families in source villages.

Nuapada district is further divided into five blocks, namely, Nuapada, Komna, Sinapali, Khariar and Boden. We randomly selected Khariar block for the purpose of the survey. A list of Gram Panchayats (GP) in the block was procured in consultation with a local civil society organization and a sub-group of GPs, which were accessible by road, were short-listed. Four Gram Panchayats (GP) were chosen randomly and in each of them, up to a maximum of three villages were chosen with at least one village which had an operational seasonal hostel in 2018-19. Our final sample comprised of seven villages which spanned over four GPs. Out of the seven villages, four villages had operational seasonal hostels in 2018-19 and three villages did not. Each of the surveyed villages had a government school[8] which provided elementary education.

We collected data by triangulating school records with data collected from household survey. Information on test scores in mid-term and end-term examinations were collected for children studying in classes 3-5 in the academic year 2018-19 through school visit. We calculate percentile rank based on child's test scores to find out the relative performance of the child in his or her respective class. This is a widely used method in the literature as an indicator of school performance of children (Gould et al., 2004; Kuhn & Weinberger, 2005; Lipscomb, 2007; Zhang et al., 2014; Zhao et al., 2014). It makes the performance comparable across different subjects, different grades and classes, different periods and across different cohorts.

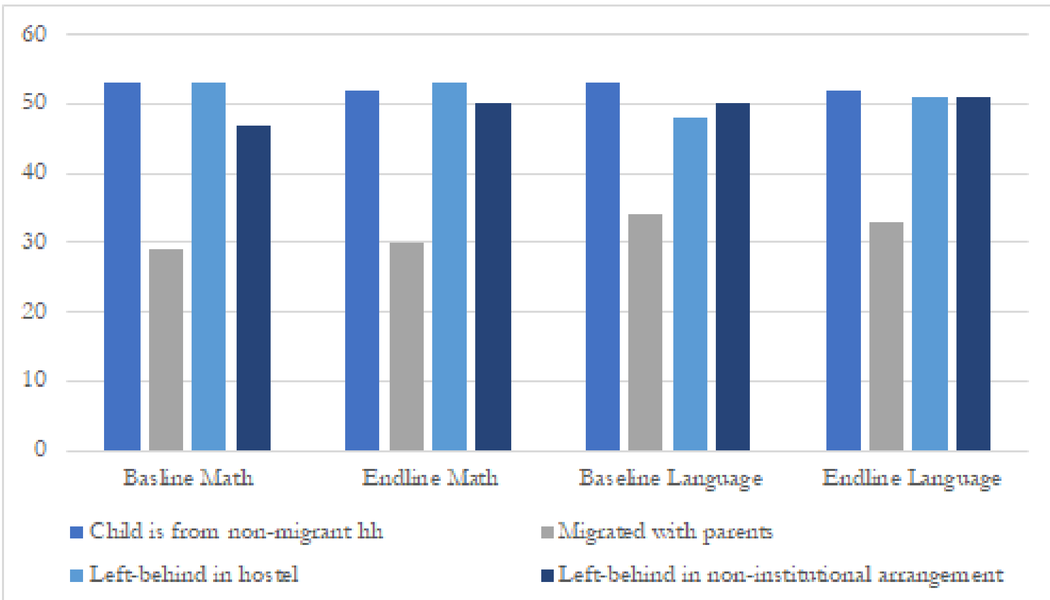
Following the school visit, a household survey was conducted to collect information of the household members. We collected information about migration status of household members, education of parents of the child, social group composition and religion of household, possession of land and television set and main source of income in the year preceding the survey. Households who reported having a migrant member in the family in 2018-19 were asked whether they had migrated with the child, whether they had left their children behind in the seasonal hostel or with other family members.

[8] There were no private schools in or around the villages

4.2 Descriptive Statistics

Our overall sample had information on 288 children. Half of the children in our sample were from households had at least one member who had migrated the year before. An examination into differences in learning outcomes shows that mean percentile rank in both mathematics and language was lower in case of children from migrant families (Figure 1).

Figure 1: Percentile rank based on test scores of children by their living arrangement

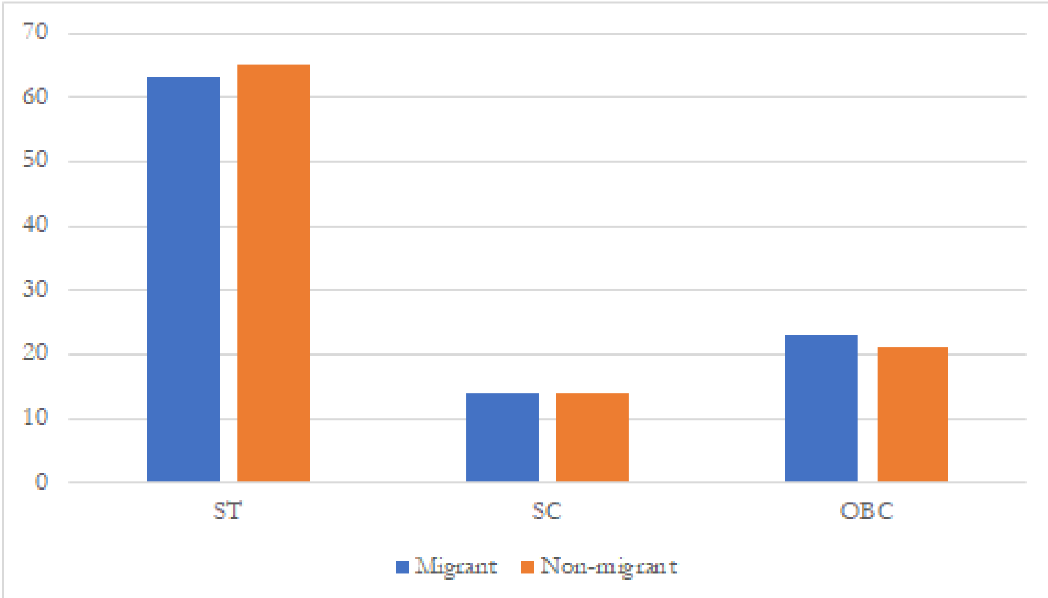


Source: Author's calculation using data collected from primary survey

The surveyed villages were mainly Hindu dominated. Six of the seven villages surveyed had only social groups of SC, ST and OBC in their population composition. At an all India level a higher proportion of ST and SC population undertake short-term migration. In our sample the social group composition was not different for migrant and non-migrant families (Figure 2).

We find that percentage of households who possessed land was higher among non-migrant families (Figure 3). This is in line with the literature which states that landless households are more prone to short-term migration relative to households that possess land. We find that a higher share of mothers in migrant households was illiterate: 73 per cent of the mothers in migrant households were illiterate compared to 69 per cent in non-migrant households. The same pattern was seen in father's education as well, as 55 per cent of the fathers in migrant households were illiterate compared to 39 per cent in non-migrant households. Even at an

Figure 2: Classification of households by social groups



Source: Author's calculation using data collected from primary survey

all-India level short-term migrant are less educated than the non-migrants (Srivastava, 2011).

4.3 Method

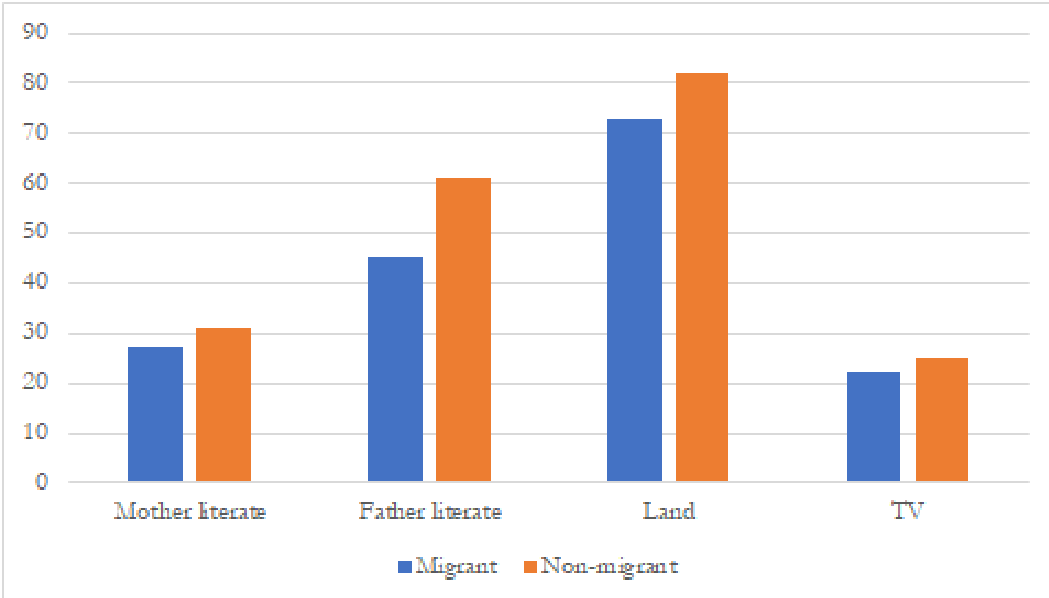
We estimate an OLS model to examine the changes in percentile rank of children based on their living arrangement, controlling for individual, household and village fixed effects. Formally we estimate the following equation where the outcome variable Y_{ihv} denotes child's percentile rank in class in mathematics and language.

The variable LB_{ihv} takes the value 0 if a child is from a non-migrant family (base category), 1 if the child had out-migrated, 2 if child was left behind in hostel and 3 if child was left behind in non-institutional arrangement.

$$\begin{aligned} Y_{ihv} = \alpha + \beta_1 LB_{ihv} + \beta_2 HH_{hv} + \beta_3 Child_{ihv} + \beta_4 Teacher_{iv} \\ + \beta_5 Baseline_{ihv} + \gamma_v + \epsilon_{ihv} \end{aligned} \tag{4}$$

Additional controls for child characteristics, $Child_{iv}$, include grade, gender of the child and whether the child attended private tuition or not. The household characteristics include social group, possession of TV and land, education level of mother and type of work the

Figure 3: Classification of households by literacy levels and possession of land and television



Source: Author's calculation using data collected from primary survey

household was engaged in. In addition we control for characteristics of teacher in $Teacher_{iv}$. We account for teacher's age, educational qualification, experience and consider a dummy for permanent work status. We control for baseline percentile rank to account for child's initial performance level. We control for village fixed effects (γ_v) and robust standard errors clustered at village level are estimated.

4.4 Result

We examine the variation in end-line percentile rank of language and mathematics of children by their living arrangement during the months of migration. The results are presented in Table 8. In columns 1-2 we include all children, irrespective of whether their parents migrated or someone else out-migrated from the family. In columns 3-4 we limit our exercise to those children whose parents had out-migrated for short term.

In all the models, the end-line percentile ranks are positively and significantly related to the baseline percentile ranks in their respective subjects. Our main interest variable is the variation in percentile rank by living arrangements of children. As the base category we consider children who are from non-migrant families, who were living with their parents. Relative to these children, percentile rank of children who were left behind in hostel or in non-institutional arrangement are not different. Children who had out-migrated had 11 and 16 percentile lower rank in mathematics and language respectively, relative to children from non-migrant families.

The control variables had different impact on percentile rank. Mother's educational level impacted percentile rank of mathematics. Possession of television at home resulted in higher percentile rank in language but not in mathematics. Child's attendance in tuition did not have any significant effect on their performance. The characteristics of teachers – teacher's age, gender, experience or work status that is temporary or permanent did not have any significant effect[9].

The overall results suggest that the children who were left behind performed as well as the children from non-migrant families. This could have happened through uninterrupted school and regular classes. On the other hand, learning outcomes of migrant children suffered due to their periodic absence from school.

Table 8: Variation in percentile rank of children by migration status of family members

	Any family member migrated or no one migrated		Parents migrated or no one migrated	
	End line percentile rank in			
VARIABLES	Math	Language	Math	Language
	(1)	(2)	(3)	(4)
Baseline percentile rank	0.504***	0.341***	0.499***	0.326***
	(0.056)	(0.058)	(0.059)	(0.062)
Base: Child is from non-migrant household				
Child migrated	-10.614*	-14.561**	-10.305*	-15.690**
	(5.423)	(6.235)	(5.646)	(6.423)
Left behind: hostel	0.064	1.674	-0.014	1.685
	(3.842)	(4.233)	(3.859)	(4.315)
Left behind: non-institutional arrangement	1.766	-0.234	4.692	-1.021
	(4.364)	(4.062)	(4.783)	(4.355)
Female	-4.287	-2.062	-4.367	-2.129
	(2.846)	(3.166)	(2.933)	(3.317)
Class 3				
Class 4	-0.178	-0.497	-0.464	1.058
	(4.059)	(4.259)	(4.112)	(4.413)
Class 5	1.078	-0.135	0.415	1.473
	(3.945)	(4.530)	(4.014)	(4.708)
Mother illiterate				
Mother literate	8.248**	6.033	7.031*	6.675
	(3.639)	(4.000)	(3.809)	(4.124)

[9]Goel and Barooah (2018) examined the role of teachers in students in forming grade 12 test scores in public schools in New Delhi. The study did not find any effect of teacher's experience, qualification or training on children's performance.

Table 8 Continued				
	Math	Language	Math	Language
ST				
SC	4.284	11.697**	6.307	12.127**
	(6.137)	(5.201)	(6.023)	(5.372)
OBC	3.685	10.358**	4.467	11.552**
	(4.504)	(4.427)	(4.741)	(4.718)
Possesses TV	4.204	8.147**	3.755	7.258*
	(4.152)	(4.029)	(4.339)	(4.210)
Possesses Land	-1.146	1.351	-0.428	2.665
	(3.701)	(3.852)	(3.857)	(3.989)
Cultivation				
Labour	7.722**	5.859	8.632**	6.456*
	(3.291)	(3.617)	(3.396)	(3.790)
Others	3.899	-1.815	4.606	-1.975
	(5.237)	(6.044)	(5.376)	(6.129)
Child attended tuition	3.153	6.118	3.541	5.171
	(3.588)	(3.809)	(3.644)	(3.941)
Female teacher	0.664	2.187	-2.077	-1.096
	(7.184)	(8.152)	(7.701)	(8.768)
Teacher is permanent	4.457	4.614	-7.556	4.650
	(16.484)	(20.714)	(19.015)	(25.378)
Teachers' experience (years)	-0.310	-0.251	0.600	-0.250
	(1.456)	(1.886)	(1.617)	(2.195)
Constant	14.044	14.700	21.765	18.186
	(13.463)	(16.039)	(15.187)	(18.886)
Village Fixed Effects	Yes	Yes	Yes	Yes
Observations	288	288	272	272
R-squared	0.406	0.274	0.412	0.265

Source: Author's calculation from primary survey. Robust standard errors clustered at the household level are presented in parenthesis. Level of significance ***<1%, **<5% and *<10%

4.5 Examining Differential Effects

As a further check, we divide the children into two groups depending on their migration status. In the first group we include children who had not migrated. This group includes children who were from non-migrant families as well as children from migrant families who were left behind: in hostels or in non-institutional arrangement. In the second group we consider children who had out-migrated. Thus our variable of interest is binary, which takes the value 0 if the child had out-migrated and 1 if the child was in the source village. We use the same methodology as used before and consider all children in our sample. The results are presented in Table 9.

We find that children in source villages had scored 11 percentile higher rank in mathematics and 15 percentile higher rank in language, relative to children who had out-migrated. The control variables are comparable to the ones obtained before.

Table 9: Variation in percentile ranks by child was in source village or child had out-migrated: all households

	End line percentile rank in	
	Math	Language
Baseline percentile rank	0.501***	0.340***
	(0.056)	(0.058)
Child migrated		
Child was in source village	11.351**	14.727**
	(5.081)	(5.865)
Constant	3.080	0.045
	(14.862)	(17.952)
Village Fixed Effects	Yes	Yes
Control Variables	Yes	Yes
Observations	288	288
R-squared	0.405	0.273

Source: Author's calculation from primary survey. Robust standard errors clustered at the household level are presented in parenthesis. Level of significance ***<1%, **<5% and *<10%

It could be argued that this result is driven by children who are from non-migrant families. A more important question would be to check the variation in children's learning levels, where all the children were from short-term migrant families. To test the same, we only consider children from migrant families. We classify the children into two groups - children who were left behind, in hostels or in non-institutional arrangement, and children who had out-migrated. Thus our variable of interest is binary. It takes the value 0 if the child had out-migrated and takes the value 1 if the child was left behind in the source villages. We present the results in Table 10.

The estimates suggest that even if we restrict our analysis to children from migrant families, children who were left-behind in the source villages outperform migrant children in both mathematics and language. Children who were left behind had 12 percentile higher rank in mathematics and 14 percentile higher rank in language compared to children who had out-migrated. These results suggest that leaving a child behind in source villages is a better alternative in order to retain their learning levels.

Table 10: Variation in percentile ranks by child was in source village or child had out-migrated: migrant households

	End line percentile rank in	
	Math	Language
Baseline percentile rank	0.583***	0.394***
	(0.075)	(0.077)
Child migrated		
Child was in source village	12.511**	14.259**
	(5.736)	(6.073)
Constant	-2.603	10.976
	(19.081)	(21.295)
Village Fixed Effects	Yes	Yes
Control Variables	Yes	Yes
Observations	145	145
R-squared	0.512	0.342

Source: Author's calculation from primary survey. Robust standard errors clustered at the household level are presented in parenthesis. Level of significance ***<1%, **<5% and *<10%

As a robustness check, we test for omitted variable bias in the estimates obtained from Tables 9 and 10. The results are presented in Table 11. We find that in both the cases, the bias adjusted β falls within the 95 per cent confidence interval of the initial estimate. Moreover, the estimated value of δ in the last column is always greater than 1. Results suggest that the impact of omitted variables on reading levels must be 5 times the influence of observed variables so that the effect of staying behind in source villages is zero. This suggests that our results are not affected by omitted variable bias.

Table 11: Assessment of potential bias due to unobserved factors: Primary Survey

	Uncontrolled (R_2)	Controlled (R_2)	Identified (Estimated bias)	
			β for $\delta = 1$ or -1	δ for β =0
	(1)	(2)	(3)	(4)
	Variable of interest: Child was in source village or child migrated			
Mathematics	21.07	11.35	[7.418, 14.85]	2.46
	(0.039)	(0.405)	(15.5)	
Reading	18.7	14.726	[13.09, 16.16]	5.09
	(0.03)	(0.273)	(2.67)	
	Variable of interest: Child was left-behind or child migrated			
Mathematics	21.01	12.51	[8.21, 16]	2.27
	(0.07)	(0.512)	(21.4)	
Reading	18.5	14.25	[11.95, 16.07]	3.2
	(0.06)	(0.342)	(5.33)	

Source: Author's calculation. Uncontrolled coefficient is obtained from the regression of learning levels on variable of interest as mentioned but without any other covariate. Controlled coefficient includes all covariates. The result is obtained using the command 'psacalc' in Stata following Oster (2019).

As the final check, we examine the variation in percentile rank among children from migrant families, with the base category of migrant children. More specifically, we examine how left-behind children in seasonal hostels and in non-institutional arrangement perform relative to migrant children. The results are presented in Table 12. We find that relative to migrant children, left-behind children in hostels have higher percentile rank, even higher than children who were left behind in non-institutional arrangement. The increase in percentile rank is more evident in the case of language.

Table 12: Variation in percentile rank of children by living arrangement of children

	Any family member migrated or no one migrated		Parents migrated or no one migrated	
	End line percentile rank in			
VARIABLES	Math	Language	Math	Language
	(1)	(2)	(3)	(4)
Baseline percentile rank	0.504***	0.390***	0.565***	0.344***
	(0.056)	(0.077)	(0.083)	(0.086)
Child migrated				
Child was in hostel	12.996*	16.296**	14.537*	20.083***
	(7.026)	(7.253)	(7.697)	(7.575)
Child was in non-institutional care	12.387**	13.683**	14.31**	15.291**
	(6.006)	(6.311)	(6.542)	(6.799)
Constant	-2.729	10.439	10.925	13.352
	(19.007)	(21.145)	(21.500)	(25.373)
Village Fixed Effects	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes
Observations	145	145	129	129
R-squared	0.512	0.343	0.548	0.345

Source: Author's calculation from primary survey. Robust standard errors clustered at the household level are presented in parenthesis. Level of significance ***<1%, **<5% and *<10%

Overall, our results suggest that operating seasonal hostels and encouraging household members to leave their children behind can be a way of protecting child's learning outcomes.

5 Conclusion

In the recent years considerable policy attention has been devoted to improving learning outcomes of children in India. The Central Government amended the Right of Children to Free and Compulsory Education Rules in 2017 to prepare class-wise and subject-wise learning outcomes for all elementary classes. More recently, National Education Policy 2020 set a goal of achieving foundational reading and numeracy for all children in grades five and above by 2025 and equal learning outcomes across all gender and social categories by 2030. In this paper we focused on a sub-group of children belonging to short-term migrant families, who require additional policy attention to retain their learning levels. We provided a quantitative assessment of the effect of short-term migration on learning outcomes of children and found that learning levels were lower for children belonging to rural short-term migrant families.

However, there are strategies to protect right to education of children from migrant families. Our primary survey examined one such strategy, viz. operating seasonal hostels in high out-migration prone villages in Odisha. The results indicate that leaving children behind in source villages could be a way of protecting their learning outcomes. Thus, depending on the context and pattern of migration, state governments can consider adopting this strategy in the months of migration.

In the future, studies need to examine and compare different strategies which aim to protect right to education of children from short-term migrant families. Besides assessing the learning levels of children, studies could assess the psycho-social support required by these children. The need of the hour is to recognise the challenges faced by these children and customise strategies based on their lived reality. The Working Group of Migration indicates that short-term migration is likely to increase in the future. The collective responsibility of governments and policymakers would be to ensure that these children do not fall behind when India aims for universal education and better learning levels for all children.

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A Appendix

Table A1: Learning levels of children when parents out-migrate for short-term

VARIABLES	Odds Ratio		LPM Coefficients	
	Math	Read	Math	Read
	(1)	(2)	(3)	(4)
Child is from non-migrant hh				
Parent migrated	0.707**	0.780*	-0.050**	-0.055**
	(0.113)	(0.102)	(0.023)	(0.028)
Age of child	0.444***	0.761***	-0.148***	-0.061***
	(0.014)	(0.018)	(0.005)	(0.005)
Female Child	0.828***	0.966	-0.034***	-0.008
	(0.046)	(0.048)	(0.010)	(0.011)
Household size	0.984	0.991	-0.002	-0.002
	(0.015)	(0.013)	(0.003)	(0.003)
Log MPCE	1.623***	1.686***	0.086***	0.116***
	(0.100)	(0.093)	(0.011)	(0.012)
Religion (Hindu)				
Muslim	0.616***	0.558***	-0.085***	-0.132***
	(0.062)	(0.049)	(0.017)	(0.019)
Others	0.944	1.050	-0.011	0.011
	(0.172)	(0.174)	(0.033)	(0.035)
Household type				
Cultivation/ allied				
Agricultural wage labour	0.909	0.823**	-0.016	-0.045**
	(0.086)	(0.071)	(0.016)	(0.019)
Non-Agricultural wage labour	0.825**	0.787***	-0.031**	-0.054***
	(0.065)	(0.054)	(0.013)	(0.015)
Organised/ business/ salaried	1.380***	1.364***	0.063***	0.069***
	(0.135)	(0.121)	(0.019)	(0.020)
Others	1.222**	1.184**	0.039**	0.038**
	(0.109)	(0.096)	(0.016)	(0.018)
ST				
SC	1.319**	1.210*	0.043**	0.044**
	(0.146)	(0.121)	(0.018)	(0.021)
OBC	1.447***	1.755***	0.059***	0.128***
	(0.150)	(0.164)	(0.017)	(0.020)
Others	1.452***	1.701***	0.062***	0.121***
	(0.172)	(0.181)	(0.020)	(0.023)
Female household head	0.938	0.941	-0.011	-0.014
	(0.086)	(0.077)	(0.016)	(0.018)
Age of household head	1.005**	1.006***	0.001**	0.001***
	(0.002)	(0.002)	(0.000)	(0.000)
Mother is illiterate				
Mother is literate	1.207***	1.313***	0.034***	0.062***
	(0.076)	(0.075)	(0.011)	(0.013)
Constant	15.264***	0.094***	0.992***	-0.029
	(9.322)	(0.050)	(0.109)	(0.119)
State Fixed Effects	Yes	Yes	Yes	Yes
Observations	7,450	7,482	7,452	7,484
R-squared			0.177	0.106

Source: Author's calculation from IHDS-II data. Robust standard errors are presented in the paranthisis. Level of significance ***<1%, **<5%, *<10%