Does the Effect of Internal Migration on Skills depend on the Age at Migration? Evidence from Four Developing Countries

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Abstract

Previous studies in developed countries have looked at the age at migration as an element that affects the impact of international migration on educational *attainment*. However, little is known about the role of age on the effect of internal migration on educational *achievement*. In this article, I posit that migration can be seen not only as a productivity shifter in the production function of cognitive and psychosocial skills, but also, and more importantly, as an input in itself since it may have a direct effect on skills. In order to test this, I use household fixed effects and Two-Stage Least Squares estimation exploiting novel data on sibling pairs during childhood and adolescence in Ethiopia, India, Peru, and Vietnam. I find suggestive evidence that the direct effect of age at migration on cognitive skills is negative, which supports the claim that sensitive periods for migration exist at earlier ages. However, results for psychosocial skills are more mixed.

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1. Introduction

At a time when there is rising concern about the future of work due to a fast-paced technological progress (World Bank, 2019) and rapid urbanisation – especially in developing countries – (Gollin *et al.*, 2016), there is an increasing need to address the challenge of preparing the future workforce for a constantly changing and highly competitive environment. Moreover, they need to be lifelong learners in order to adapt and thrive under these circumstances. Thus, building key cognitive and psychosocial skills among children today is the basis for preparing them to succeed tomorrow. If left aside, the cost of low human capital would be tremendous and, therefore, the need to invest in skills – by improving households, schools, and local environments – becomes a pressing issue for governments and families.

In this context, one way to develop human capital could be to migrate: by changing their place of residence, individuals can modify their investments and environments so that skills may be altered – although the direction of this change is unknown a priori (Franco Gavonel, 2018). This leads to an important question about the timing of migration: does age at migration matter? In the last two decades, a growing number of studies looked at the effect of age at immigration, mainly to Northern European countries and the US, on children's educational attainment (Böhlmark, 2008; Chiswick & DebBurman, 2004; Gjefsen & Galloway, 2013; Hermansen, 2017; Lemmermann & Riphahn, 2018; Ohinata & van Ours, 2012; van den Berg *et al.*, 2014). These studies find a negative association between age at immigration and educational outcomes, mainly schooling.

However, more schooling does not necessarily lead to more skills and despite there is a "learning crisis" around the world (Kaffenberg & Pritchett, 2017; World Bank, 2018), there is a lack of studies on the impact of age at arrival on the educational achievement of migrants. Moreover, the studies mentioned above focus on international migration to developed countries and, to my knowledge, there is no evidence on internal migration in developing countries – which is surprising given that internal migration is more prevalent than international migration, especially in this context (Bell & Charles-Edwards, 2013). In this paper, I address these gaps and test whether age at migration affects the impact of internal migration on skills among children and adolescents in developing countries.

In order to address potential bias in previous studies, this article uses household fixed effects and Two-Stage Least Squares (FE-2SLS) using temperature and rainfall in the children's place of residence as instruments for migration. I exploit within-family variation from a rich data set on children and their siblings aged 18 years old or less from the Young Lives study in Ethiopia, India (Andhra Pradesh and Telangana), Peru, and Vietnam. It must be noted that, as shown in my conceptual framework, in this article I estimate a conditional demand for skills, which correspond to the *total* effect of age at migration on skills. Following Todd and Wolpin (2003) and Glewwe and Miguel (2008), this effect can be decomposed on a *direct* effect – namely, the one that would be estimated through a production function – and *indirect* effects that result from behavioural responses to migration – which can be observed or unobserved. Furthermore, if we assume that the unobserved input responses have the same sign as the observed ones, we can infer the sign of the direct effect.

The skills considered in the analysis are cognitive – Peabody Picture Vocabulary Test (PPVT)[1] – and psychosocial – Agency, Pride, and Self-esteem. Both types of skills are important predictors of future economic and social behaviour (Heckman *et al.*, 2006). It is also well documented that skills formation processes vary in their malleability at different ages in such a way that there are sensitive and critical periods for their acquisition[2] (Cunha *et al.*, 2006). Therefore, it is not surprising to expect that there may be periods during which migration is better undertaken.

[1] The PPVT is used in all countries, except for India, where the Mathematics test was administered instead.
[2] Sensitive periods can be broadly defined as stages of the technology of skill formation that are more productive in producing some skills than other stages, whereas critical periods are those in which only one stage alone can produce a given skill.

On one hand, there is vast evidence that shows that some inputs should be applied preferably in the earliest years since their return is higher during this period as basic skills are just being established and neural circuits are most plastic (Knudsen *et al.*, 2006). Thus, we would expect a negative effect of age at migration as younger migrants are expected to perform better than older ones. On the other hand, it is plausible to expect that moving at a very early age may be disruptive for the child as they move away from relatively secure communities. Also, this is consistent with a new wave of research – mainly on developmental science – that finds that adolescence may be a second "window of opportunity" for growth and learning (Dahl *et al.*, 2018; Fuhrmann *et al.*, 2015; Knoll *et al.*, 2016; Sheehan *et al.*, 2017; Steinberg, 2014). Moreover, although the intelligence quotient (IQ) results can be affected by environmental factors only up to age 8-10, achievement test scores may still be affected over a much greater range of ages (Cunha *et al.*, 2006).[3] Thus, we could also expect a positive effect of age at migration on skills.

In this study, I find evidence that supports the former hypothesis. In Ethiopia, younger migrants perform better in PPVT than their older counterparts; however, in Peru children that migrated at an older age obtain a higher PPVT score than their younger siblings. Meanwhile, in India and Vietnam I find no effect of age at migration. In order to find potential mechanisms that explain these results, I look at the effect of age at migration on highest grade attained of sibling pairs. I find that age at migration has a positive effect on school attainment in Ethiopia and Peru. Putting together these results allows me to do important inferences regarding the impact of age at migration on cognitive skills: given that the observed input response is positive in Ethiopia, but the total effect is negative, we can infer that the direct effect is negative and is larger than the indirect effect. On the contrary, in Peru the observed input response dominates the direct effect and, therefore, I obtain a positive total effect. In India and Vietnam, indirect unobserved effects are at least as large as the direct effect. In sum, we can infer that the direct effect of age at migration is negative, which supports the claim that sensitive periods for migration exist at earlier ages, although the exact period goes beyond the scope of this paper.

Regarding psychosocial skills, results are more mixed: younger migrants outperform their older counterparts on Agency scores in Ethiopia. Following the same reasoning as above, we can infer that the direct effect of age at migration on Agency is negative, supporting too the hypothesis of sensitive periods during early years. Overall, these results are important to inform policymakers on two dimensions: first, how to tailor initiatives that encourage migration of families with children, and second, how to facilitate their corresponding assimilation to the host locality through education.

The remainder of the paper is organised as follows. Section 2 describes the context of each of the study countries, specifically the main characteristics of each education system. Section 3 presents a conceptual framework that briefly illustrates the relationship between migration and skills. Section 4 describes the empirical strategy of the paper. Section 5 introduces the data and some key descriptive statistics. Section 6 describes the main results, section 7 presents a discussion and section 8 concludes.

[3] It must be noted that achievement tests capture crystallised intelligence rather than fluid intelligence, which is better captured by IQ tests. In addition, the former tends to increase monotonically over the life course, whereas the latter tends to peak in early adulthood and then declines (Almlund *et al.*, 2011).

2. Context

This section presents a brief description of the educational systems in each of the study countries in order to depict the different settings at which this study takes place. This is important to understand the different incentives that potential migrants may have to decide when to migrate.

In three of the four countries, the length of basic education, including preschool, is 15 years, whereas in Peru it is only 14 years – see Table 1. Nonetheless, the starting point varies: in Ethiopia, the preschool year starts one year after it does in India, Peru, and Vietnam. Therefore, the total amount of basic education also ends one year later than in the other three countries. The division of basic education into different phases is most accentuated in India, where both Primary and Secondary are split into lower and upper stages. On the contrary, Peru is the country that does not have any division regarding these. Moreover, in Ethiopia education is compulsory until Grade 8. Similarly, in India it is mandatory until the age of 14 (Grade 8). In Peru, since 1996 education is compulsory for children up to age 16, which includes Preschool, Primary, and Secondary levels. In Vietnam, mandatory education used to go up to Grade 5, but in 2005 this changed and at the moment it goes up to Grade 9 (World Education News and Reviews, 2019).[4]

In three of the four countries, pupils should sit for general exams at the end of some levels of education in order to test whether they are able to continue to the next level. In Ethiopia there is the Elementary School Leaving Certificate Examination after Grade 8, the Ethiopian General Secondary Education Certificate Examination after Grade 10, and the Ethiopian Higher Education Entrance Certificate Examination after Grade 12. Similarly, in India there is the Year 10 Certificate, which comes after Secondary Education and the Year 12 Certificate after completion of Upper Secondary Education. In Vietnam, there is only the Secondary School Graduation Examination, which takes place after Grade 12. Finally, in Peru there is no general examination at any point of basic education.

However, looking at the actual rates of educational attainment gives us a more accurate view of the educational systems. Table 2 shows the share of population above 25 with no schooling. It ranges from 5 per cent in Peru to 75 per cent in Ethiopia. Although the net enrolment ratio in primary education in all countries is high (85 per cent and above), the graduation rates from secondary education are also sparse: they range from 9 per cent in Ethiopia to 85 per cent in Peru. This pattern is also evidenced in the mean years of schooling.

3. Conceptual Framework

This section lays out a framework that illustrates the relationship between children's skills and migration at different ages that is central to this study. The aim of the proposed framework is threefold: first, it will outline the mechanisms through which migration affects skills; second, it will guide the empirical specification to be estimated by eliciting its main assumptions; and third, it will flag potential shortcomings in the estimation of the effects of interest. It is an adaptation of the model presented in Todd and Wolpin (2003) that conceives a child's skill as an outcome of a cumulative process of knowledge acquisition in which current and past inputs[5] are combined with the child's endowment or learning efficiency. With this specification of the skills' production function, I then derive a conditional demand for skills in order to show explicitly the equation to be estimated in section 4. The framework's key contributions are to incorporate migration as the variable of interest into the standard framework of skills formation highlighting the existence of critical and sensitive periods, as well as to allow the effect of migration on skills to vary across different stages of skills development.

[4] According to UNESCO Institute for Statistics (2019), the current number of compulsory years of schooling in Vietnam is 10 instead of 9.

[5] I implicitly define inputs as all factors that have a direct impact on skills, whereas investments are a subset of inputs. For example, in value-added specifications, lagged skills would be inputs, rather than investments.

As a first step, assume that S_{iha}^{v} denotes the skill v of child i residing with family h at age a, and it is determined by the following production function – namely, the structural relationship that expresses output (skills) as a function of inputs (endowments, investments, and environments).

$$S_{iha}^{v} = S_{a,F}^{v}[I_{ih}(a), M_{ih}(a), \mu_{ih0};\ SH_{ih}(a), M_{ih}(a)] \tag{1}$$

where v stands for cognitive or psychosocial skills; $I_{ih}(a)$ denotes the histories of three subset of inputs (those supplied by the child's family, school and local environment) up to age a (Glewwe & King, 2001);[6] $M_{ih}(a)$ denotes the history of migration and implies that migration experienced by the child depends on age a, which reflects the importance of the timing of migration since moving at different developmental stages may have differential effects on skills; μ_{ih0} stands for the child's endowed mental capacity, which includes factors such as ability and motivation; $SH_{ih}(a)$ denotes a vector of productivity shifters and their histories, such as parental education, school quality, and social interactions. Furthermore, the a subscript in $S_{a,F}^{v}[\,]$ allows for the effect of investments, migration and endowment to vary with the age of the child, whereas the F subscript stands for production function of skills.

Migration is defined as a change in locality of residence and it is included twice in equation (1) because it is assumed to be both an input – it affects skills directly, namely $\frac{\partial S_{iha}^{v}}{\partial M_{iha}} \neq 0$ – and a productivity shifter – it affects them indirectly by influencing the productivity of other inputs, namely $\frac{\partial^2 S_{iha}^{v}}{\partial M_{iha} \partial I_{iha}} \neq 0$, where it is assumed that migration takes place before the application of investments when the child is aged a. A similar proposition was posited earlier by Cunha *et al.* (2006) when they apply the concepts of self-productivity – that the stock of past skills is an input in the production of skills in the next stage – and direct complementarity – that higher past skills increase the productivity of inputs in the next period – to the production of human capital. As an analogy to the stock of skills, I argue that migration is an input in itself and it also affects the productivity of other inputs. This is the main departure from the framework outlined by Franco Gavonel (2018), where migration is assumed to be only a productivity shifter.

Generally, migration is expected to change the level of inputs I_{iha}; more specifically, as a result of migration, at least the subset of inputs provided by the local environment will change.[7] Normally, migrating would also involve a change in the subset of school inputs.[8] In addition, if the child moves alone or if the household arrangements are affected by migration (e.g. the mother enters the labour market), she may even have changes in the three subsets of inputs.

However, the key point here is that migration is an input because its effect should not only be viewed as a mere change in the level of investments, but also as a change in *who* provides them. For example, a child may move with her family from one city to another without the level (or quality) of inputs being altered. Nevertheless, the sole act of *changing* actors (e.g. new teachers, classmates, neighbours, etc.) and environment, beyond the aspect of it that directly affects the provision of other inputs, calls for a process of adaptation that requires effort and may have a direct effect on the child's skills.

[6] Following Cunha *et al.* (2006), this assumes that investments are general in nature, namely that they affect both cognitive and psychosocial skills – thus, they do not require a superscript v.
[7] Strictly speaking, change in environment could also mean that the child's current environment changed due to war, invasion, dictatorship, or departure from a dictatorship. Glewwe and King (2001) also argue that parents' collective action may change the local environment.
[8] In the developing world, this may not necessarily be the rule since it is possible that a child that lives in a remote village attends school in the nearest town, and even if he migrates to another remote village, he may still attend the same school in town. See Lucas (1997) for a reference pointing that rural-rural migration is the most prevalent type of movement in developing countries.

For example, new social norms require the child to adapt not only at school, but in the new community. Glewwe and King (2001) include cultural norms as one of the determinants of external stimulation; specifically, as part of educational characteristics of the local environment, together with school quality and availability. In this line, it could be argued further that cultural norms may affect all aspects of the child's life beyond the scholastic aspect and, therefore, it makes the process of adaptation more urgent. Moreover, moving to a place where a different language is spoken is likely to affect the child beyond the educational sphere since it entails a process of adaptation that requires effort, regardless of the level of proficiency that the child may already have on that language.[9]

The sign of this effect – or the *ceteris paribus* effect holding other inputs constant (Todd & Wolpin, 2003) – is ambiguous[10] as it could promote the child's skills acquisition if he is comfortable with the change of environment or, alternatively, it could prevent him from acquiring more skills as a result of having migrated. The size of this effect, though, is likely to depend on the severity of the change in environment (i.e. on the cultural and socio-economic distance between the place of origin and the place of destination) conditional on the child's personality traits and preferences related to openness to new experiences[11] (i.e. loosely speaking, the former reflects how much he *can* adapt, while the latter reflects how much he *enjoys* adapting). The inclusion of personality traits implies that psychosocial skills may also be contained within equation (1) as inputs, which is consistent with the concepts of self- and cross-productivity discussed above (Cunha *et al.*, 2006).

This direct effect of migration is compounded by the fact that, as mentioned before, it normally also leads to different levels of investments, which may result in indirect effects of migration. Note, however, that these indirect effects should also account for, as in the case of the direct effects, the impact of a relatively large *change* in inputs on skills since the more dramatic the change in inputs (regardless of the sign) as a result of migration, the more the child has to adapt to. Thus, the more negative this effect on skills would be, at least in the short run. Ideally, in the long run, if the change in inputs were positive, it would be expected that the child would adapt and "catch-up" with the natives in the destination place – though this proposition remains to be tested as it goes beyond the scope of this study.

Provided that migration implies a change in actors and general environment, it is reasonable to expect that migration is also a productivity shifter since it will affect the marginal productivity of investments in the current or subsequent periods as they are synergistic.[12] For instance, following the example of the child that migrates without having the level (or quality) of inputs changed, we could still expect that one hour at school with new teachers and classmates will now produce a different amount of skills than without migrating. The sign of this effect, however, remains ambiguous and should be tested empirically.

The estimation of equation (1), nevertheless, is difficult due to the non-observability of the endowment and the incomplete data on the history of inputs. One way to circumvent the latter is to substitute the investments for their direct determinants following Glewwe and Miguel (2008) and Franco Gavonel (2018). Maximising the household utility subject to a budget constraint and the technology presented in equation (1), yields the following reduced form demand for investments:

[9] Of course, if it is a completely new language for the child, this will likely affect his learning process in different subjects at school, but even if this is not the case and he already comes to the new place with some proficiency of it, the sole process of moving to a place where a different language is used in daily life requires adaptation. For a brief discussion on the role of language in educational achievement of immigrants see Ohinata and van Ours (2012).

[10] In this framework, it is not impossible for an input – in this case, migration – to have a negative effect on the output since this is also the case of the role of the incidence of infectious diseases as part of the local health environment in the health production function according to Glewwe and Miguel (2008) or the effect of risky behaviours, such as smoking or stressful lifestyles as part of the vector of inputs in the health production function according to Strauss and Thomas (2008).

[11] These are defined as the tendency to be open to new aesthetic, cultural, or intellectual experiences (Almlund *et al.*, 2011).

[12] This relates to the role of migration as a productivity shifter in equation (1).

$$I_{iha} = I_{a,D}[P_h(a), SH_{ih}(a), W_{h0}, \sigma_h, \mu_{ih0}, r_h] \quad (2)$$

where $P_h(a)$ denotes the history of prices of all inputs (investments and migration); W_{h0} stands for initial household wealth; σ_h is a parameter for parental preferences that are fixed over time; and r_h is an interest rate at which parents can borrow. The subscript D in $I_{a,D}$ stands for reduced form demand for skills.

Following Pollak (1969), migration can be treated as fixed in the short run at its utility maximising level (M^*_{iha}) at the age at which investments are applied. Thus, from equation (2) we obtain the following demand for investments conditional on migration:

$$I_{iha} = I_{a,CD}[M^*_{iha}; P'_h(a), SH_{ih}(a), W'_{h0}, \sigma_h, \mu_{ih0}, r_h] \quad (3)$$

where $P'_h(a)$ denotes the history of inputs' prices excluding the price of migration, and W'_{h0} stands for income net of expenditure on migration. The CD subscript in $I_{a,CD}$ stands for conditional demand for investments. Equation (3) implies that conditional on migration, the realised levels of exogenous variables up to age a are also fixed. Therefore, it excludes the price and expenditure on migration, which are subsumed in M^*_{iha}. Then, substituting equation (3) in equation (2) yields the following demand for skills conditional on migration:

$$S^v_{iha} = S^v_{a,CD}[M^*_{iha}; P'_h(a), SH_{ih}(a), W'_{h0}, \sigma_h, \mu_{ih0}, r_h] \quad (4)$$

where the CD subscript in $S^v_{a,CD}$ stands for conditional demand for skills. Following Todd and Wolpin (2003) and Glewwe and Miguel (2008), we can assert that equation (4) uncovers the total effect of migration on skills, which captures both direct and indirect effects.

This framework tells us that migration affects skills depending on the age at which it took place, and it does so through three channels: i) as an input of the production function – shown in equation (1); ii) as a productivity shifter and as an element that affects other productivity shifters – also shown in equation (1); and iii) by affecting the level of inputs – shown in equation (3). As a result, the total effect of migration on skills is ambiguous, since the level and productivity of some investments may increase whereas those of other investments may decrease as a result of migration.

4. Empirical Strategy

The aim of this study is to estimate the difference in skills between older and younger migrants between ages 3 to 18, which allows me to consider sensitive periods during childhood and adolescence. In order to do this, I exploit a rich dataset on sibling pairs – see next section for more details on this –, which allows me to compare two siblings of different ages at the same calendar time.[13]

Following Todd and Wolpin (2003), I will present the set of challenges and assumptions needed to estimate equation (4) under some data limitations. Assuming an additively linear specification, the empirical analogue of equation (4) can be expressed as:

$$S_{ihat} = \alpha^a_1 M_{ihat} + \alpha^a_2 F_h + \alpha^a_3 \mu^c_{ih0} + \boldsymbol{\alpha'^a_4 P'_h(a)} + \boldsymbol{\alpha'^a_5 SH_{ih}(a)} + \omega_{ihat} \quad (5)$$

[13] The Young Lives data do not allow to match sibling pairs of same age at different calendar times since this procedure results on a very small sample. Moreover, the fact that in Ethiopia, India, and Vietnam the sibling can be older than the index child makes this task even more difficult to achieve.

where S_{ijat} is a variable for cognitive or psychosocial skills S of child i aged a residing with family h in period t – a new dimension added to equation (4). M_{ihat} is a binary variable that takes the value of 1 if the household – which includes both siblings – migrates between periods $t-1$ and t.[14] Endowed mental capacity can be decomposed into a heritable family-specific component (μ_{h0}^{f}) and an orthogonal child-specific component (μ_{ih0}^{c}) such that a single household effect (F_h) can be defined as $F_h = \mu_{h0}^{f} + W_{h0}' + \sigma_h + r_h$. Also, ω_{ihat} is an error term that includes measurement error and any random factors beyond parents' control that may have affected skills at age a. Finally, α_1^a, α_2^a, and α_3^a are parameters, whereas α_4^a and α_5^a are coefficient vectors.

The first challenge to estimate equation (5) by ordinary least squares (OLS) is that we do not observe permanent factors, such as F_h and μ_{ih0}^{c}, which are correlated with migration. This issue arises if parents have some fixed characteristics that make them more prone to migrate and to provide inputs that facilitate learning to their children. For example, they may be more motivated and would be more likely to move and to help their children with homework. In order to address this, I use within-family estimators that exploit data from siblings at same calendar time t, but different ages (a and a'), so that all elements – both time variant and time invariant – common to both siblings are differenced out.[15] The analogue of equation (5) for sibling i' aged a' would be:

$$S_{i'ha't} = \alpha_1^{a'} M_{i'ha't} + \alpha_2^{a'} F_h + \alpha_3^{a'} \mu_{i'h0}^{c} + \boldsymbol{\alpha'}_{\boldsymbol{4}}^{\boldsymbol{a'}} \boldsymbol{P}_{\boldsymbol{h}}'(\boldsymbol{a}') + \boldsymbol{\alpha'}_{\boldsymbol{5}}^{\boldsymbol{a'}} \boldsymbol{SH}_{\boldsymbol{i'h}}(\boldsymbol{a}') + \omega_{i'ha't} \tag{6}$$

Assuming that the household-fixed component is independent of age (namely that $\alpha_2^a = \alpha_2^{a'} = \alpha_2$) and subtracting equation (6) from (5) yields:

$$S_{ihat} - S_{i'ha't} = \alpha_1^a M_{ihat} - \alpha_1^{a'} M_{i'ha't} + \alpha_3^a \mu_{ih0}^{c} - \alpha_3^{a'} \mu_{i'h0}^{c} + \cdots + \omega_{ihat} - \omega_{i'ha't} \tag{7}$$

As mentioned above, migration is assumed to be a family input, namely that each pair of siblings move – or stay – together with the household ($M_{ihat} = M_{i'ha't} = M_{ht}$). Then, equation (7) would be:

$$S_{ihat} - S_{i'ha't} = \left(\alpha_1^a - \alpha_1^{a'}\right) M_{ht} + [\alpha_3^a \mu_{ih0}^{c} - \alpha_3^{a'} \mu_{i'h0}^{c} + \cdots + \omega_{ihat} - \omega_{i'ha't}] \tag{8}$$

where the error term contains all the elements in square brackets. This implies that differencing between siblings only cancels out the family-specific endowment, whereas the child-specific one is still in the error term. Furthermore, it is very likely that parents' decision to migrate take into account child heterogeneity and intra-household allocation of resources is made considering child-specific endowments and outcomes of *both* children. Thus, in order to deal with the remaining endogeneity of migration, I utilise 2SLS estimation: I use the price of migration as instrument since it is an element that affects M_{ht}, but that is excluded from the conditional demand in equation (4) and the error term in equation (8). As a proxy for the price of migration, I use weather shocks at the place of origin and their quadratic form – see Franco Gavonel (2018) for more details on the latter. I assume that weather variation alters the monetary and non-monetary costs of migration and, therefore, its price, which in turn affect the decision to migrate. This identification strategy is expected to produce consistent estimates of migration on skills as long as the weather shocks only affect skills through their effect on the decision to migrate. This empirical strategy is also expected to deal with bias resulting from random measurement error in the variable of migration.

[14] Since the Young Lives study does not collect a migration history of the sibling, I cannot observe his date of migration. Therefore, I assume that if the household moves, both siblings move too. As it will be explained in the next section, I cannot observe individual migration, so the results on this study only hold for households who have remained together.

[15] It must be noted that since I am looking at household migration, each pair of siblings are exposed to the same amount of time in the destination place, namely, same time of migration and same time of assessment.

Given the aim of this study and the data availability, the actual estimation of equation (5) would be based on the following equation:

$$S_{iht} = \beta_0 + \beta_1 M_{ht} + \beta_2 M_{ht} * A_{iht} + \beta_3 F_h + \boldsymbol{\beta'_4 X_{iht}} + \boldsymbol{\beta'_5 H_{ht-1}} + \boldsymbol{\beta'_6 L_{ht-1}} + \varepsilon_{iht} \quad (9)$$

where A_{iht} stands for age at the time of migration; X_{iht} is a vector of child characteristics that contains the child's gender, birth order, and ethnicity;[16] H_{ht-1} is a vector of household characteristics that includes parental education and household wealth; L_{ht-1} is a vector of location variables such as the region of origin and whether the origin locality is urban; X_{iht}, H_{ht-1}, and L_{ht-1} account partly for $P'_h(a)$ and $SH_{ih}(a)$; ε_{iht} is an error term that includes all the omitted factors (e.g. any random factors beyond parental control that may have affected scores, the child-specific component of the endowment which is unknown to the parents until some time after birth, and measurement error). β_0, β_1 and β_2 are parameters, whereas β_4 and β_5 are vectors of parameters. The key assumption of this specification is that the age at migration affects *linearly* the impact of migration on skills.

Differencing across siblings (index child i and her sibling i') in order to remove all elements common to both of them, yields the analogue of equation (7):

$$\Delta S_{ht} = \beta_2 M_{ht} * \Delta A_{ht} + \boldsymbol{\beta'_4 \Delta X_{ht}} + \Delta\varepsilon_{ht} \quad (10)$$

where ΔS_{ht} is the difference in skills between siblings in household h in period t; ΔA_{ht} is the difference in age at migration between siblings which is equivalent to the difference in dates of birth, since it is assumed that both siblings were affected by the decision to migrate (or not) at the same time; ΔX_{ht} is a vector that captures the differences in gender and birth order between siblings; and $\Delta\varepsilon_{ht}$ is the difference in the idiosyncratic error between siblings. Please note that differencing also eliminates household migration, household characteristics, and locality terms since they are common to both siblings and it is assumed that they have a common effect between siblings. Looking at equation (4), this procedure also differences out the history of prices and expenditure on migration since these are assumed to be common between siblings. In addition, the inclusion of gender and birth order – as part of X_{ht} – accounts partly for differential parental investments between siblings. For instance, parents may spend more in tuition on boys than on girls (Rosenzweig & Schultz, 1982) or, alternatively, on the first child (Price, 2008).

As mentioned above, once household heterogeneity is accounted for, we are still left with child heterogeneity: parents can still choose to migrate after observing the learning efficiency or endowments of their children (Glewwe *et al.*, 2001). For instance, they may either reinforce (Becker & Tomes, 1976) or compensate (Behrman *et al.*, 1982) differences in ability between siblings by choosing to migrate if it favours one of them. Then we would have that $E[M_{ht} * \Delta A_{ht}, \Delta\varepsilon_{ht}] \neq 0$ which leaves us still with endogeneity of migration. This concern will be addressed by estimating equation (10) by 2SLS using as instruments for migration rainfall and temperature deviations from the historical mean at the place of origin. These weather shocks (C_{ht-1}) are expected to be uncorrelated with children's endowments (ε_{iht} and $\varepsilon_{i'ht}$), so that $E[C_{ht-1}\, \Delta\varepsilon_{ht}] = 0$, and they would only affect their skills through migration.

Another reason to implement this empirical strategy is that there may be measurement error in the indicator of migration. Specifically, if this error is uncorrelated with the true migration variable – namely, there is a classical errors-in-variables –, then it would lead to attenuation bias in the OLS estimation of β_2 in equation (10) and I would be underestimating the true β_2. However, the use of weather shocks as instrumental variables would address this problem.

Given that migration is a binary indicator, I follow Wooldridge (2002) and Angrist and Pischke (2009) to circumvent the forbidden regression problem – namely, substituting a nonlinear function of an

[16] As it will be explained in the next section, equation (9) does not include age because the scores have already been standardised by age. This allows for a more flexible relationship between age and scores (not only linear).

endogenous variable with the same nonlinear function of fitted values from a first-stage estimation. The proposed strategy then is to first estimate an auxiliary probit model of migration on all the instruments and the same covariates used in the OLS model – namely, the vectors X_{iht}, H_{ht-1}, and L_{ht-1} in equation (9). Then, take the fitted value resulting from this estimation, interact it with ΔA_{ht}, and use it as an instrument for the interaction of migration and age at migration in the 2SLS estimation. It is worth noticing that this procedure results in an exactly identified model where the interaction of the fitted value and the difference in age at migration is the only instrument used in the estimation of 2SLS.

Still, following Glewwe *et al.* (2001), one main criticism remains to this identification strategy. There is a possibility that weather shocks affect household income – considering that between 27 and 79 per cent of the sample live in rural areas – so that this might alter the provision of educational inputs, which may, ultimately, affect skills. Although this is an inherent weakness of my empirical strategy, at least I can speculate with the direction of the bias. On one hand, weather shocks may drive out families from their place of origin increasing the likelihood of migrating. In the case that they also impair mental development, this would induce a negative correlation between C_{ht-1} and ε_{iht}, leading to underestimate β_2. On the other hand, weather shocks may actually make families use all possible resources to resist the shocks in their place of origin, decreasing the likelihood of migration and, ultimately, overestimating β_2. Whether it is the former or the latter explanation that prevails remains an empirical question – see section 6 for more details on this.

Lastly, in order to explore one potential mechanism that may explain how the age at migration affects the impact of migration on skills, I look at the child's school attainment. This yields:

$$\Delta G_{ht} = \theta_2 M_{ht} * \Delta A_{ht} + \boldsymbol{\theta'_3} \Delta \boldsymbol{V_{ht}} + \Delta\mu_{ht} \tag{11}$$

where ΔG_{ht} denotes the difference between siblings in the highest grade completed; ΔV_{ht} is a vector that contains the differences in gender, birth order and age (in 2013) between siblings;[17] θ_2 is a parameter and θ_3 is a vector of parameters. Specifically, I look at the empirical analogue of equation (3) following the same identification strategy I used to estimate equation (4).

5. Data and Descriptive Statistics

This section presents a succinct description of the data used in this study, as well as a summary of the key variables used in the analysis.

5.1 Data Sources

The data used in this paper comes from Young Lives (YL), a longitudinal study that collects information on children every three years between 2002 and 2013 since they were 1 year old up to 12 years old in Ethiopia, India (Andhra Pradesh and Telangana), Peru, and Vietnam.[18] Since round 3 (2009), YL also collects data on one sibling that could be either older or younger than the index child.[19] For the analysis of this paper, I restricted the sample to keep only siblings aged 18 or below – the results remained unchanged and although they are not shown in the next section, they could be provided upon request. As discussed in Franco Gavonel (2017), attrition is relatively low as it ranges between 0.6 and 2.1 per cent in each country – see Table 3 for a summary of sample size, attrition, ages, and dates per round.

Except for Peru, where the sample is nationally representative, the YL sample is representative of poor youth. Specifically, the sampling methodology consisted of a multi-stage sampling procedure, where

[17] Note that the difference in covariates between equations (11) and (12) is that ΔV_{ht} contains ΔX_{ht} since the former includes age in round 4.
[18] Although the study consists of two cohorts of children, in this paper I only use the data corresponding to the younger cohort – children born in 2000 and 2001.
[19] Only in Peru, exclusively younger siblings were selected.

sentinel sites were chosen according to a set of pro-poor criteria. In turn, households with at least one child born on 2000-01 within a sentinel site were randomly selected (Escobal & Flores, 2008; Kumra, 2008; Nguyen, 2008; Outes-Leon & Sanchez, 2008).

The data on precipitation and temperature were provided by the Global Climate Database of the University of Delaware (UDEL), which was matched to the localities where children lived in rounds 3 and 4 – see Georgiadis (2017) for more details.[20]

5.1 Internal Migration and Age

Migrants are defined as those who reside in a different locality[21] in round 4 (2013) than in round 3 (2009) – a period during which the index children in the sample were between 9 and 12 years old, respectively, and their siblings were 18 or below – regardless of where they lived during the intervening years. Similarly, non-migrants are those who reside in the same locality in rounds 3 and 4, even if they lived elsewhere in between. Thus, migration was captured by a binary indicator if the child's community identifier changed between these rounds. In the remainder of this paper, this definition will be labelled as household migration, which is the definition used for the analysis. This is different than child migration as reported in the child's migration history of the survey, which includes both household *and* individual migration. Therefore, the inferences made in this study hold only for household migration, but not for all types of migration. Table 4 compares these definitions and shows the overlap between the two of them. The lowest rate is almost 70 per cent, which is reasonable for my purposes. Table 5 summarises the streams of migration. Urban-urban migration is the most frequent stream in Ethiopia and Peru, whereas rural-rural is the most predominant in India. In Vietnam, both are equally prevalent.

The age at migration of each pair of siblings was calculated using the date of move from the migration history section of the household questionnaire – provided they had undertaken household migration. Specifically, in order to calculate the difference of the interaction of movement and age at migration ($M_{ht} * \Delta A_{ht}$), I used as an equivalent measure of ΔA_{ht} the difference in the dates of birth of the pair of siblings given that the date of migration is assumed to be common to both children.[22] Table 6 shows the sibling-paired sample with the rest of the YL sample. In Ethiopia and Vietnam, households in the paired sample are less likely to migrate than in the full sample. Table 7 compares descriptive statistics across siblings. On average, except for Vietnam, the index children migrated at an older age than their siblings. Figure 1 presents the distribution of the age at migration of index children and their siblings. Except for Vietnam, the age at migration of the index child peaks at 10 and 11 years, whereas that of the sibling peaks at 7 in Ethiopia and Peru and at 5 in Vietnam.

5.2 Cognitive and Psychosocial Skills

Cognitive skills in Ethiopia, Peru, and Vietnam are expressed by a measure of receptive vocabulary, namely Peabody Picture Vocabulary Test (PPVT) collected in round 4 of the survey – see Cueto and Leon (2012) for more details on the test. It consists of slides with four pictures presented to the child, from which they have to choose the one that best represents the word named by the enumerator. It is considered a measure of receptive vocabulary because children do not need to name the objects themselves and they do not need to read or write (Schady *et al.*, 2015). The score was calculated as the percentage of correct answers and then it was standardised by age within country to have a mean of zero and a standard deviation of one.

Unlike in the previous countries, cognitive skills in India are expressed by a measure of mathematics. The test consists of a series of questions about basic arithmetic operations and a set of problems that

[20] I am deeply grateful to Dr. Andreas Georgiadis for having matched these data with the Young Lives data.
[21] Locality is defined as a kebele in Ethiopia, a village/ward in India, a district in Peru, and a commune in Vietnam.
[22] In the YL survey, there is no date of migration for the panel sibling. Therefore, this was imputed, as mentioned above, under the assumption that both children moved with the rest of the household.

require reading and solving. The score was also calculated as the percentage of correct answers, and then standardised by age within country to have a mean of zero and a standard deviation of one.

Psychosocial skills were captured by measures of agency, pride, and self-esteem. Agency can be defined as an individual's sense of control over their own life (Rotter, 1966). Self-esteem can be defined as a person's assessment of their self-worth, and its measure is based on Shavelson *et al.* (1976). Finally, pride is a concept related to that of self-esteem (Rosenberg, 1965), although it is linked to specific domains such as school, work, clothing, and housing (Dercon & Krishnan, 2009). Each index was constructed by first standardising each relevant item by age within country to have a mean of zero and a standard deviation of one, and then taking the average of all the corresponding items – for more details, see Franco Gavonel (2018).

As shown in Table 6, index children from the paired sample have a different performance on PPVT – better in India and worse in the other three countries – than the rest of the sample. A second difference lies on the agency score: in Ethiopia and Peru, children in the paired sample perform worse than those in the rest of the sample, whereas in India, the opposite holds. These two stylised facts suggest that my analysis could be based on a selected sample. Nevertheless, to the extent that I assert that my results are representative of relatively poor households with at least two children, sample selection need not be a particular concern.

As seen in Table 7, in all countries, the index children have attained a higher grade than their sibling. However, the former perform worse in PPVT than the latter in Ethiopia and Peru. In psychosocial scores, there is no significant difference between the two.

5.3 Weather Shocks

As discussed in section 3, in order to assess whether the impact of migration varies with the age at migration, I exploit exogenous variation in migration arising from weather shocks. These shocks are defined as precipitation and temperature deviations from the community and season average between rounds 3 and 4 (over the period 1950-2014). Specifically, the variables used for the analysis correspond to rainfall and temperature shocks averaged over each half of the year of the index child's life between the ages of 8 and 12 (the period between rounds 3 and 4, which is the one when household migration occurs). These deviations from the norm are used as a proxy for weather shocks that affect the household – given that this is my variable of interest. Still, as we will see in the next section, they are good predictors of household migration.

Recently there has been a growing body of literature dedicated to the study of the effect of environmental change on migration (Falco *et al.*, 2018). The results are mixed and are more scant when it comes to relate this phenomenon with child migration.

6. Results

As explained in section 4, in order to estimate the difference in skills between older and younger migrants, I first estimated a probit model of migration on the instruments – weather shocks and their quadratic form – and the covariates from the OLS regression.[23] Table A.1 shows the results for each country. The shocks that are significant in Ethiopia, India, and Peru are mainly those that are increasing on the level of rainfall or temperature and are concave – namely, the coefficient of the shock in levels has a positive sign often accompanied by a negative squared term. Vietnam is the exception to this observation as weather shocks follow primarily a decreasing and convex function. It must be noted that

[23] A word of caution: this is an auxiliary regression – not a first-stage one – to calculate the predicted value of migration, which will then be used as an instrument for the 2SLS estimation.

the literature that looks at the relationship between weather variation and migration is also inconclusive (Falco *et al.*, 2018).

Table 8 presents the results obtained from estimating equation (10) for cognitive and psychosocial skills. For each country, the first column shows the results using OLS estimation, the second column using within-family estimation (FE, hereafter), and the third one using household fixed effects and 2SLS estimation (FE-2SLS, hereafter) – which is my preferred specification. Before interpreting the point estimates, I will first present the 2SLS diagnostics. At the bottom of the table lies the Kleibergen-Paap rk Wald F statistic (KPF-statistic, hereafter), which tests for weak instruments with non-i.i.d. errors. In all countries, the KPF-statistic is above the rule of thumb of 10 posited by Staiger and Stock (1997) and in most cases, above the critical values proposed by Stock and Yogo (2005). This suggests the rejection of the null hypothesis of weak instruments.

Turning to the analysis of the variables of interest in Panel A of Table 8, in Ethiopia I find that age at migration has a negative effect on PPVT, namely that younger migrants perform better than older ones. On the contrary, in Peru older migrants outperform their younger counterparts, whilst in India and Vietnam I find no effect of age at migration. It must be noted that the direction of the bias in the OLS estimates also varies by country. Except for Vietnam, the OLS estimates are positive and greater than the FE estimates. This implies that children living in households with characteristics that are positively correlated with PPVT scores – for example, better-off households – are more likely to migrate. This leads to an overestimation of the OLS point estimates. Furthermore, when comparing the FE with the FE-2SLS estimates, we observe that in Ethiopia, India, and Vietnam the former is larger than the latter, suggesting that there is a positive bias in the FE estimates. Since FE-2SLS accounts for both household and child heterogeneity, this implies that more able children migrate at an older age.

Regarding the psychosocial skills, panel B shows a similar picture as the one described above for Ethiopia: younger migrants obtain higher agency scores than older ones. However, in panels C and D there is no differential effect of migration by age in any of the countries. A potential explanation for this could be that there may be different technologies of skills formation between cognitive and psychosocial skills – still this is something that yet needs to be tested.

In order to explore potential mechanisms that may elucidate the findings presented above, I tested whether there is a differential effect of moving on school attainment by age at migration.[24] Table 9 shows that in Ethiopia and Peru the age of migration has a positive effect on grade completion – namely, older migrants have higher school attainment than younger ones (controlling for age). This finding allows me to deduce the sign of the direct effect of age at migration on skills. Given that in Ethiopia the total effect of age at migration on cognitive skills is negative and its indirect effect on the observed input is positive, we can infer that the direct effect of age at migration on skills is negative and it dominates the indirect effects – assuming that the effect on unobserved inputs have the same sign as on the observed ones. Analogously, given that in Peru the total effect is positive, we can infer that the indirect effects are greater in magnitude than the direct ones. Lastly, for India and Vietnam, where I find no total effect or observed indirect effect, I can conclude that the unobserved indirect effect is at least as large as the direct one. A similar reasoning allows us to infer that the effect of age at migration on psychosocial skills – specifically, Agency – is negative too.

In sum, this study provides suggestive evidence that the hypothesis of sensitive periods at early ages dominates the impact of age at migration on skills. Thus, younger migrants perform better than older ones in both cognitive and psychosocial skills. However, in some contexts this may be offset or even exceeded by behavioural responses as a result of migration.

[24] I also looked at time use as an input, but my results do not show any systematic pattern on the effect of age at migration on time allocation. Table A.2 shows these results.

7. Discussion

In this article, I use FE-2SLS to identify a causal effect of age at migration on the development of cognitive and psychosocial skills. I find suggestive evidence that moving at a younger age is better in terms of skills formation, although in some contexts input responses may counteract this effect, resulting in opposite or even null effects. It must be noted, however, that a limitation of this research is that I do not estimate a production function of skills, and therefore, this paper only provides suggestive evidence rather than direct proof of existence of sensitive periods.

Another limitation of this study, nevertheless, is that I only look at household migration and do not account for individual migration. In a time when child migration is ubiquitous, increasing the risks that children and adolescents are exposed to (UNICEF, 2017), this represents an interesting avenue for further research.

8. Conclusions

Age at migration matters and the earlier a child moves the better. This is consistent with vast evidence on early years as a sensitive (or even critical) period. Although I cannot assert what is the exact age at which the effect of migration on skills peaks, I can suggest that – among poor households – moving at an earlier age within the country is more beneficial for the child than doing it at an older age.

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Figure 1: Distribution of age at migration

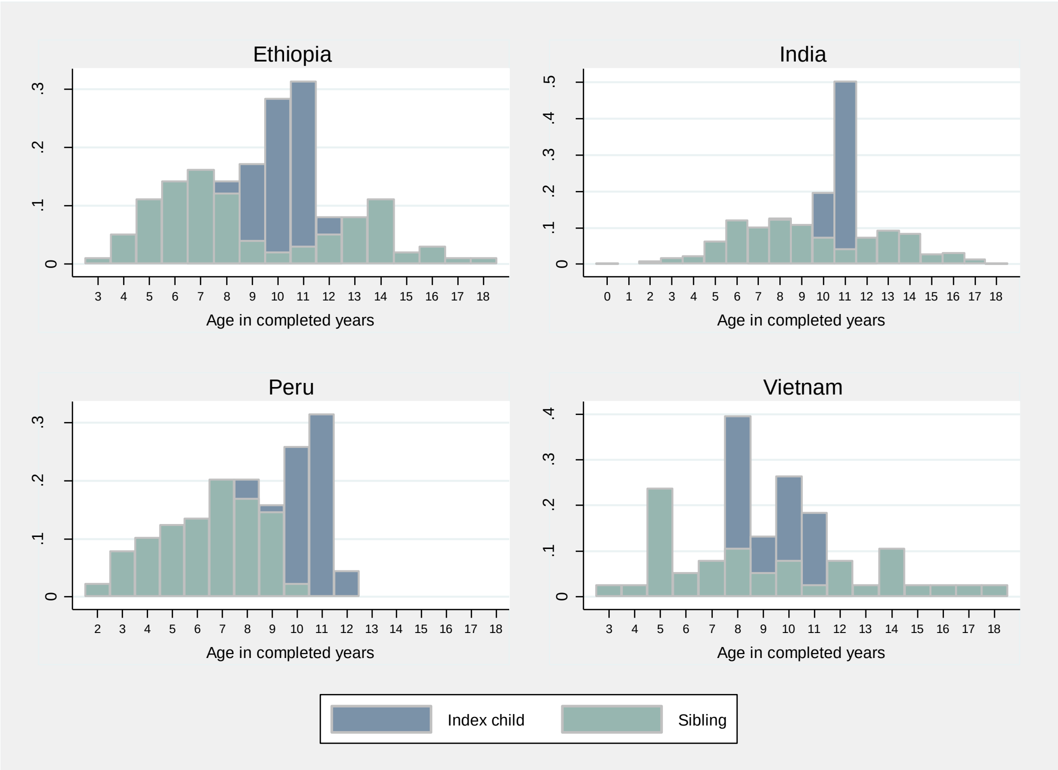

Table 1: Education system in the study countries

Age (Years)	Level			
	Ethiopia	India*	Peru	Vietnam
1				
2				
3		Preschool	Preschool	Preschool
4	Preschool			
5				
6		Lower Primary	Primary	Elementary
7	Elementary			
8				
9				
10				
11		Upper Primary		Lower Secondary
12			Secondary	
13				
14		Secondary		
15	General			Upper Secondary
16	Secondary	Upper Secondary		
17	Upper Secondary			
18				

Source: World Education News and Reviews (2019)
*Note: India refers specifically to the states of Andhra Pradesh and Telangana.

Table 2: Basic education statistics per study country

	Ethiopia	India	Peru	Vietnam
Share of population above 25 with no schooling	0.75	0.41	0.05	0.07
Net enrolment ratio in primary education	0.85	0.92	0.97	0.98
Gross graduation ratio from upper secondary education	0.09	0.33	0.85	0.54
Mean years of schooling	2.0	5.3	9.2	8.1

Source: UNESCO Institute for Statistics (2019)

Table 3: Sample of analysis

	Age of Index Child	Ethiopia		India		Peru		Vietnam	
		Index Children	Siblings	Index Children	Siblings	Index Children	Siblings	Index Children	Siblings
Round 1 (2002)	1	1,999	N.A.	2,011	N.A.	2,052	N.A.	2,000	N.A.
Round 2 (2006)	5	1,912	N.A.	1,950	N.A.	1,963	N.A.	1,970	N.A.
Round 3 (2009)	8	1,885	1,552	1,931	N.A.	1,943	576	1,961	1,155
Round 4 (2013)	12	1,873	1,541	1,915	1,651	1,902	799	1,932	981
In Rounds 3 and 4		1,868	1,513	1,912	N.A.	1,884	555	1,924	981
Attrition between rounds 3 and 4		0.6%		0.8%		2.1%		1.5%	

Note: The age of the index child is measured in years. This sample sizes include index children and their siblings irrespective of whether they have data on cognitive and psychosocial scores. The number of siblings was calculated taking into account the siblings ID assigned to them in each round.

Table 4: Migration rates in each round of Young Lives survey

	Ethiopia			India			Peru			Vietnam		
	Household migration	**Child Migration**	**Overlap**	**Household migration**	**Child Migration**	**Overlap**	**Household migration**	**Child Migration**	**Overlap**	**Household migration**	**Child Migration**	**Overlap**
Ever moved in any round	0.15	N.A.	N.A.	0.21	N.A.	N.A.	0.52	N.A.	N.A.	0.14	N.A.	N.A.
Between R1 and R2	0.02	N.A.	N.A.	0.05	N.A.	N.A.	0.35	N.A.	N.A.	0.07	N.A.	N.A.
Between R2 and R3	0.04	N.A.	N.A.	0.03	N.A.	N.A.	0.23	N.A.	N.A.	0.03	N.A.	N.A.
Between R3 and R4	0.14	0.08	0.86	0.19	0.23	0.69	0.20	0.11	0.85	0.07	0.06	0.96

Note: Household migration is defined as a change in community ID between rounds, whereas child migration is recorded in the child's migration history and it is defined as any change in locality that lasted at least 1 month in Vietnam, 2 months in Ethiopia and India, and 3 months in Peru. The overlap shows the share of children that moved (or stayed) according to both definitions.

Table 5: Streams of migration, conditional on place of origin

	Ethiopia		India		Peru		Vietnam	
Rural-Rural	0.63	80	0.65	160	0.49	49	0.74	42
Rural-Urban	0.38	48	0.35	88	0.51	51	0.26	15
Urban-Rural	0.17	22	0.30	34	0.08	23	0.02	1
Urban-Urban	0.83	108	0.70	78	0.92	251	0.98	43
N		258		360		374		101

Note: Each cell in the odd columns show the probability of moving to a given area conditional on the place of origin. For example, the probability of moving to a rural area conditional on living in another rural area in Ethiopia is 0.63. Therefore, the sum of the two cells corresponding to each type of move is 1.

Table 6: Characteristics of YL Sample

Variable	Sibling-Paired Sample			Rest of YL Sample			Difference (p-value)
	Mean	SD	Count	Mean	SD	Count	
Ethiopia							
PPVT score	-0.16	0.99	1008	0.31	0.92	330	0.0000
Agency score	-0.02	0.55	1280	0.06	0.53	277	0.0274
Pride score	-0.02	0.66	1281	0.05	0.63	277	0.1018
Esteem score	0.01	0.62	1280	-0.02	0.61	277	0.4523
Migrated	0.04	0.18	1285	0.07	0.25	273	0.0089
Age (months)	145.22	3.94	1285	145.82	3.67	273	0.0208
Male	0.52	0.50	1285	0.55	0.50	273	0.3408
First born	0.14	0.35	1285	0.56	0.50	273	0.0000
Father's education	4.33	4.08	1285	6.48	4.91	273	0.0000
Caregiver's education	2.44	3.43	1285	3.97	4.27	273	0.0000
Wealth index	0.31	0.16	1285	0.37	0.17	273	0.0000
Urban	0.31	0.46	1285	0.59	0.49	273	0.0000
Enrolled in school	0.94	0.24	1285	0.96	0.19	273	0.1178
Highest grade completed	3.37	1.79	1285	3.81	1.72	273	0.0002
India							
Math score	0.03	0.99	1222	-0.21	1.04	319	0.0002
Agency score	0.01	0.51	1304	-0.08	0.46	273	0.0151
Pride score	-0.01	0.62	1319	-0.06	0.59	259	0.1724
Esteem score	0.01	0.61	1322	-0.07	0.57	257	0.0531
Migrated	0.06	0.24	1341	0.07	0.26	242	0.4088
Age (months)	143.60	3.80	1341	143.98	3.94	242	0.1548
Male	0.54	0.50	1341	0.54	0.50	242	0.9722
First born	0.35	0.48	1341	0.53	0.50	242	0.0000
Father's education	5.56	5.07	1341	5.43	5.20	242	0.7023
Caregiver's education	3.58	4.48	1341	3.43	4.56	242	0.6402
Wealth index	0.51	0.18	1341	0.49	0.19	242	0.2002
Urban	0.24	0.43	1341	0.23	0.42	242	0.5794
Enrolled in school	0.97	0.16	1340	0.98	0.13	242	0.3183
Highest grade completed	5.44	1.30	1340	5.49	1.39	242	0.5362
Peru							
PPVT score	-0.19	1	656	0.12	0.99	892	0.0000
Agency score	-0.06	0.52	640	0.05	0.50	906	0.0001
Pride score	-0.04	0.63	644	0.03	0.60	904	0.0368
Esteem score	-0.01	0.57	649	0.01	0.58	900	0.4380
Migrated	0.09	0.29	662	0.08	0.28	891	0.5151
Age (months)	143.06	3.64	662	142.84	3.66	891	0.2359
Male	0.50	0.50	662	0.51	0.50	891	0.6779
First born	0.39	0.49	662	0.33	0.47	891	0.0168
Father's education	8.28	3.91	662	9.50	3.72	891	0.0000
Caregiver's education	6.97	4.24	662	8.37	4.34	891	0.0000
Wealth index	0.48	0.20	662	0.59	0.20	891	0.0000
Urban	0.64	0.48	662	0.81	0.39	891	0.0000
Enrolled in school	1	0.00	661	1.00	0.06	886	0.1344
Highest grade completed	6.01	0.99	661	6.12	0.88	886	0.0233

			Vietnam				
PPVT score	-0.09	1.06	847	0.09	0.91	898	0.0001
Agency score	-0.01	0.53	830	0.00	0.55	927	0.6088
Pride score	-0.01	0.57	830	0.01	0.58	927	0.3322
Esteem score	0.02	0.57	831	-0.01	0.56	926	0.4179
Migrated	0.03	0.16	872	0.06	0.23	888	0.0016
Age (months)	146.24	3.73	872	146.38	3.69	888	0.4185
Male	0.49	0.50	872	0.54	0.50	888	0.0329
First born	0.36	0.48	872	0.57	0.50	888	0.0000
Father's education	6.94	4.05	872	8.08	3.76	888	0.0000
Caregiver's education	5.91	3.95	872	7.57	3.68	888	0.0000
Wealth index	0.58	0.20	872	0.62	0.17	888	0.0000
Urban	0.20	0.40	872	0.18	0.39	888	0.5028
Enrolled in school	0.97	0.16	871	0.98	0.12	888	0.1201
Highest grade completed	5.57	0.97	872	5.72	0.78	888	0.0004

Note: Each score was measured in 2013, as well as enrolment and highest grade completed. The rest of covariates were measured in 2009. The sample of each score corresponds to the number of children that has data on that score, whereas the sample of each covariate corresponds to the number of children that has data on that covariate and in *any* of the scores. Migration is defined as household migration.

Table 7: Characteristics of the Sibling-Paired Sample (2013)

Variable	Index Child			Sibling			Difference (p-value)
	Mean	SD	Count	Mean	SD	Count	
Ethiopia							
PPVT score	-0.16	0.99	1008	-0.01	0.99	1008	0.0010
Agency score	-0.02	0.55	1280	-0.03	0.55	1280	0.8589
Pride score	-0.02	0.66	1281	-0.01	0.66	1281	0.6877
Esteem score	0.01	0.62	1280	-0.01	0.62	1280	0.4960
Age (months)	145.22	3.94	1285	130.38	40.56	1285	0.0000
Age at migration (months)	124.49	13.86	96	111.46	43.28	96	0.0055
Male	0.52	0.50	1285	0.51	0.50	1285	0.5024
First born	0.14	0.35	1285	0.08	0.26	1285	0.0000
Enrolled in school	0.94	0.24	1285	0.86	0.35	1209	0.0000
Highest grade completed	3.37	1.79	1285	2.65	2.87	1204	0.0000
Age at enrolment	93.65	21.06	1217	87.09	22.13	1012	0.0000
India							
Math score	0.03	0.99	1222	-0.01	0.99	1222	0.3598
Agency score	0.01	0.51	1304	-0.01	0.53	1304	0.3623
Pride score	-0.01	0.62	1319	0.00	0.66	1319	0.7609
Esteem score	0.01	0.61	1322	-0.02	0.64	1322	0.1963
Age (months)	143.60	3.80	1341	139.01	37.23	1341	0.0000
Age at migration (months)	127.37	14.14	354	119.04	41.72	354	0.0004
Male	0.54	0.50	1341	0.49	0.50	1341	0.0149
First born	0.35	0.48	1341	0.29	0.45	1341	0.0001
Enrolled in school	0.97	0.16	1340	0.95	0.23	1293	0.0004
Highest grade completed	5.44	1.30	1340	5.05	3.09	1288	0.0000
Age at enrolment	63.65	9.48	1331	63.56	10.17	1248	0.8122
Peru							
PPVT score	-0.19	1	656	-0.01	1.01	656	0.0010
Agency score	-0.06	0.52	640	0.00	0.45	640	0.0307
Pride score	-0.04	0.63	644	-0.01	0.6	644	0.4735
Esteem score	-0.01	0.57	649	-0.02	0.57	649	0.8134
Age (months)	143.06	3.64	662	104.61	15.18	662	0.0000
Age at migration (months)	123.31	14.93	80	83.79	23.09	80	0.0000
Male	0.50	0.50	662	0.48	0.50	662	0.5829
First born	0.39	0.49	662	0.00	0.00	660	0.0000
Enrolled in school	1.00	0.00	661	1.00	0.07	657	0.0821
Highest grade completed	6.01	0.99	661	2.94	1.39	657	0.0000
Age at enrolment	71.85	5.83	661	72.06	5.37	624	0.5174
Vietnam							
PPVT score	-0.09	1.06	847	-0.02	1.00	847	0.1660
Agency score	-0.01	0.53	830	-0.04	0.59	830	0.2727
Pride score	-0.01	0.57	830	0.00	0.58	830	0.6198
Esteem score	0.02	0.57	831	0.01	0.54	831	0.8205
Age (months)	146.24	3.73	872	146.14	42.00	872	0.9443
Age at migration (months)	117.97	14.73	35	113.00	48.73	35	0.5653
Male	0.49	0.50	872	0.50	0.50	872	0.7376
First born	0.36	0.48	872	0.32	0.47	872	0.1063
Enrolled in school	0.97	0.16	871	0.90	0.30	867	0.0000
Highest grade completed	5.57	0.97	872	5.34	3.55	867	0.0642
Age at enrolment	73.02	5.19	861	72.90	6.27	809	0.6886

Note: Each score was measured in 2013, as well as enrolment, highest grade completed, and age.

Table 8: Effects of Migration by Age on Skills

`	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		Ethiopia			India			Peru			Vietnam	
	OLS	FE	FE-2SLS	OLS	FE	FE-2SLS	OLS	FE	FE-2SLS	OLS	FE	FE-2SLS
Panel A - Dependent variable: PPVT Score (2013)												
Migration*AgeM	0.007	-0.005**	-0.024***	0.006	-0.001	-0.002	0.013*	0.003	0.016**	-0.022**	-0.004	-0.011
	(0.008)	(0.002)	(0.007)	(0.007)	(0.003)	(0.010)	(0.007)	(0.003)	(0.008)	(0.011)	(0.007)	(0.008)
Observations	1,008	1,008	1,008	1,222	1,222	1,222	654	654	654	847	847	847
K-P F-Statistic			12.83			25.75			36.47			51.76
Panel B - Dependent variable: Agency Score (2013)												
Migration*AgeM	0.006	-0.004*	-0.012*	-0.001	-0.001	-0.000	-0.005	0.001	0.004	-0.001	-0.001	0.002
	(0.004)	(0.002)	(0.007)	(0.004)	(0.001)	(0.006)	(0.004)	(0.002)	(0.007)	(0.007)	(0.003)	(0.006)
Observations	1,280	1,280	1,280	1,304	1,304	1,304	638	638	638	830	830	830
K-P F-Statistic			15.80			24.04			21.53			40.76
Panel C - Dependent variable: Pride Score (2013)												
Migration*AgeM	0.000	0.001	-0.001	0.003	0.002	0.002	-0.005	0.004	0.003	0.006	-0.006	0.004
	(0.007)	(0.003)	(0.010)	(0.005)	(0.002)	(0.006)	(0.005)	(0.003)	(0.011)	(0.010)	(0.005)	(0.007)
Observations	1,280	1,280	1,280	1,314	1,314	1,314	642	642	642	830	830	830
K-P F-Statistic			15.80			26.15			21.43			40.76
Panel D - Dependent variable: Self-Esteem Score (2013)												
Migration*AgeM	-0.005	0.001	-0.000	-0.002	0.003	-0.004	-0.000	0.000	-0.006	-0.007	0.005*	-0.004
	(0.005)	(0.002)	(0.007)	(0.004)	(0.002)	(0.005)	(0.004)	(0.002)	(0.006)	(0.007)	(0.003)	(0.005)
Observations	1,280	1,280	1,280	1,322	1,322	1,322	647	647	647	831	831	831
K-P F-Statistic			15.80			27.68			38.79			40.76

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All scores are standardised by age within country to have a mean of zero and a standard deviation of one. Panel A corresponds to Math Score in India. The models specification in columns (1), (4), (7), and (10) include the following covariates: migration, gender, ethnicity, birth order, father's and caregiver's education, wealth, type of locality (urban) in 2009, and region in 2009. The specification in all other columns include only the following combinations of gender and birth order: male index child and female sibling, female index child and male sibling, female index child and female sibling, eldest index child only, and eldest sibling only (except for Peru, where the index child is always older than the sibling).

Table 9: Effects of Age at Migration on Years of Schooling

	Dependent variable: Years of schooling (2013)											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		Ethiopia			India			Peru			Vietnam	
	OLS	FE	FE-2SLS	OLS	FE	FE-2SLS	OLS	FE	FE-2SLS	OLS	FE	FE-2SLS
Migration*AgeM	0.010	0.007	0.045**	0.004	-0.009	-0.004	-0.006	-0.003	0.019*	-0.003	0.003	0.009
	(0.018)	(0.007)	(0.019)	(0.008)	(0.008)	(0.020)	(0.008)	(0.005)	(0.010)	(0.011)	(0.004)	(0.014)
Observations	1,217	1,217	1,217	1,315	1,315	1,315	676	676	676	874	874	874
R-squared	0.441	0.624	0.615	0.150	0.656	0.655	0.170	0.563	0.538	0.261	0.719	0.719
K-P F-Statistic			18.55			23.99			31.06			19.24

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All models control for age in 2013 and the following combinations of gender and birth order: male index child and female sibling, female index child and male sibling, female index child and female sibling, eldest index child only, and eldest sibling only (except for Peru, where the index child is always older than the sibling). The auxiliary regression includes the previous covariates, as well as ethnicity, father's and caregiver's education, wealth, type of locality (urban) in 2009, and region in 2009.

APPENDIX

Table A.1: Effect of Weather Shocks on Migration

	(1) Ethiopia	(2) India	(3) Peru	(4) Vietnam
Male index child and female sibling	-0.174	-0.096	0.129	0.433
	(0.205)	(0.168)	(0.225)	(0.434)
Female index child and male sibling	0.086	0.096	0.282	-0.131
	(0.211)	(0.163)	(0.226)	(0.439)
Female index child and female sibling	0.032	-0.034	0.188	0.573
	(0.213)	(0.180)	(0.209)	(0.479)
Eldest index child only	0.465**	0.396***	0.234	0.593
	(0.193)	(0.141)	(0.158)	(0.406)
Eldest sibling only	-0.027	-0.232		0.194
	(0.320)	(0.178)		(0.460)
Father's education	-0.012	-0.003	0.032	-0.119*
	(0.022)	(0.014)	(0.024)	(0.063)
Caregiver's education	0.056**	0.004	-0.033	0.036
	(0.027)	(0.018)	(0.026)	(0.050)
Wealth Index (2009)	-0.891	0.256	0.186	0.101
	(0.797)	(0.559)	(0.578)	(1.226)
Urban (2009)	0.375	-0.195	0.000	-1.677*
	(0.312)	(0.228)	(0.218)	(0.879)
Rainfall shock in 1st half of year 9 after birth	0.000	0.001	0.003	-0.043**
	(0.004)	(0.001)	(0.003)	(0.017)
Rainfall shock in 1st half of year 9 after birth ^2	-0.000	-0.000	0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Rainfall shock in 2nd half of year 9 after birth	0.000	0.001	-0.003	-0.041***
	(0.005)	(0.001)	(0.003)	(0.012)
Rainfall shock in 2nd half of year 9 after birth ^2	0.000	0.000	-0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Rainfall shock in 1st half of year 10 after birth	-0.000	0.006***	0.010***	0.026
	(0.007)	(0.002)	(0.003)	(0.016)
Rainfall shock in 1st half of year 10 after birth ^2	-0.000	-0.000	-0.000**	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Rainfall shock in 2nd half of year 10 after birth	-0.006	0.004**	0.001	-0.053***
	(0.006)	(0.002)	(0.003)	(0.016)
Rainfall shock in 2nd half of year 10 after birth ^2	0.000	-0.000	0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Rainfall shock in 1st half of year 11 after birth	-0.002	0.004**	-0.001	-0.102***
	(0.004)	(0.002)	(0.003)	(0.023)
Rainfall shock in 1st half of year 11 after birth ^2	-0.000	0.000	0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Rainfall shock in 2nd half of year 11 after birth	-0.003	0.001	0.000	0.098***
	(0.004)	(0.002)	(0.002)	(0.029)
Rainfall shock in 2nd half of year 11 after birth ^2	0.000	-0.000	-0.000**	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Rainfall shock in 1st half of year 12 after birth	-0.003	-0.002	-0.002	-0.035
	(0.005)	(0.002)	(0.001)	(0.024)
Rainfall shock in 1st half of year 12 after birth ^2	-0.000*	-0.000	0.000**	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Rainfall shock in 2nd half of year 12 after birth	-0.017***	-0.000	-0.002	0.049***
	(0.004)	(0.002)	(0.002)	(0.013)

Rainfall shock in 2nd half of year 12 after birth ^2	0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Temperature shock in 1st half of year 9 after birth	-0.047	-0.159*	0.118*	-2.187*
	(0.155)	(0.088)	(0.067)	(1.304)
Temperature shock in 1st half of year 9 after birth ^2	-0.017	0.088***	-0.002	-0.150
	(0.048)	(0.030)	(0.011)	(0.212)
Temperature shock in 2nd half of year 9 after birth	0.021	0.057	0.021	-0.831
	(0.142)	(0.071)	(0.038)	(0.869)
Temperature shock in 2nd half of year 9 after birth ^2	-0.010	-0.001	0.003	-0.115
	(0.045)	(0.027)	(0.007)	(0.248)
Temperature shock in 1st half of year 10 after birth	0.444***	0.129	-0.076	-13.223***
	(0.156)	(0.110)	(0.056)	(3.462)
Temperature shock in 1st half of year 10 after birth ^2	-0.079	0.001	-0.012*	-2.336***
	(0.054)	(0.024)	(0.007)	(0.536)
Temperature shock in 2nd half of year 10 after birth	0.371***	0.165*	-0.023	10.008***
	(0.100)	(0.085)	(0.045)	(2.016)
Temperature shock in 2nd half of year 10 after birth ^2	0.041	-0.021*	-0.013	-1.006***
	(0.043)	(0.012)	(0.009)	(0.233)
Temperature shock in 1st half of year 11 after birth	0.097	0.145*	0.014	-6.483***
	(0.148)	(0.077)	(0.040)	(1.662)
Temperature shock in 1st half of year 11 after birth ^2	0.024	-0.011	-0.002	0.178
	(0.066)	(0.019)	(0.002)	(0.184)
Temperature shock in 2nd half of year 11 after birth	-0.204	0.022	0.039	1.041
	(0.196)	(0.103)	(0.045)	(1.713)
Temperature shock in 2nd half of year 11 after birth ^2	-0.020	-0.026	0.001	-0.168
	(0.063)	(0.024)	(0.003)	(0.150)
Temperature shock in 1st half of year 12 after birth	-0.549**	0.041	-0.064	2.603***
	(0.225)	(0.094)	(0.053)	(0.936)
Temperature shock in 1st half of year 12 after birth ^2	-0.008	-0.029*	0.007**	-0.206
	(0.062)	(0.017)	(0.003)	(0.152)
Temperature shock in 2nd half of year 12 after birth	-0.139	-0.100	-0.001	5.128***
	(0.171)	(0.105)	(0.047)	(1.114)
Temperature shock in 2nd half of year 12 after birth ^2	-0.039	-0.011	-0.005	0.103
	(0.058)	(0.016)	(0.005)	(0.126)
Constant	-1.485*	-0.955*	-1.824***	-32.005***
	(0.848)	(0.539)	(0.436)	(8.411)
Observations	1,008	1,222	654	847
R-squared	0.25	0.15	0.13	0.54

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All models include as covariates ethnicity and region (in 2009).

Table A.2: Effects of Age at Migration on Time Use

	(1) Sleep	(2) Caring for others	(3) Domestic tasks	(4) Work within household	(5) Work outside household	(6) At school	(7) Studying outside school	(8) Leisure
				Ethiopia				
Migration*AgeM	-0.000	-0.015	-0.015	0.000	0.034	-0.015	-0.001	-0.003
	(0.012)	(0.017)	(0.021)	(0.022)	(0.044)	(0.027)	(0.013)	(0.025)
Observations	950	676	676	676	676	676	676	950
K-P F-Statistic	8.90	21.84	21.79	21.76	21.75	21.82	21.77	8.90
				India				
Migration*AgeM	0.008	-0.007*	0.005	0.053	0.021	-0.102**	-0.016	0.021
	(0.008)	(0.004)	(0.010)	(0.039)	(0.016)	(0.049)	(0.024)	(0.017)
Observations	1,156	1,014	1,014	1,014	1,014	1,014	1,014	1,156
K-P F-Statistic	19.45	15.32	15.32	15.32	15.50	15.31	15.34	19.45
				Peru				
Migration*AgeM	0.004	0.032	-0.013	-0.051	-0.012*	0.020	-0.021	0.008
	(0.010)	(0.022)	(0.017)	(0.034)	(0.007)	(0.018)	(0.032)	(0.014)
Observations	645	454	454	453	454	454	454	645
K-P F-Statistic	32.96	10.95	11.05	10.48	11.05	11.02	11.04	32.96
				Vietnam				
Migration*AgeM	-0.005	0.010	0.011	-0.031	0.027	-0.027	0.006	-0.003
	(0.009)	(0.015)	(0.016)	(0.026)	(0.055)	(0.039)	(0.030)	(0.018)
Observations	812	603	620	620	617	615	608	812
K-P F-Statistic	34.46	18.95	27.60	27.44	27.48	27.60	26.14	34.46

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All models control for age and the following combinations of gender and birth order: male index child and female sibling, female index child and male sibling, female index child and female sibling, eldest index child only, and eldest sibling only (except for Peru, where the index child is always older than the sibling). The auxiliary regression includes the previous covariates, as well as ethnicity, father's and caregiver's education, wealth, type of locality (urban) in 2009, and region in 2009.