Maternal and Paternal Migration, and Children's Human Capital

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International migration opportunities improve earnings capacity, but can also create parental separation from children. The net effect of migration on children depends on the relative importance of money and parental presence in determining a child's human capital development, which parent migrates, and at what age they separate from the child. These considerations in turn affect whether, when, and who migrates. I estimate a dynamic model of migrant households with an embedded age-specific child education production function by conducting a panel survey of Filipino migrants and combining it with newly assembled administrative data from the Philippines Department of Education and the Department of Migrant Workers. For identification, I exploit shocks to the demand for male and female Filipino migrant workers in East Asia and the Middle East. I find monetary resources play a considerably more significant role in shaping child human capital from the ages of 11–15, whereas both maternal and paternal time inputs are more critical between the ages of 6–10. A mother's time is always substantially more productive than a father's time across all ages. Parental time and monetary inputs are always complements. Father's and mother's presence are complementary when a child is 6–10, but become substitutes at later ages. Parents internalize the effects of their absence on their children and will more likely migrate if they observe successful academic outcomes. In addition, parents are more likely to migrate when they know their children have a greater endowment of abilities that enhance academic outcomes.

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Introduction

It is estimated that there are 272 million international migrants across the globe [UNDESA, 2019]. This is a number that is only predicted to rise with increased global mobility [Clemens, 2022]. International migration opportunities often improve earnings capacity by two or threefold, but can also create parental separation from children [Mobarak et al., 2023]. For example, approximately one in every four children in the Philippines, will not have a parent physically present in their life at some point due to parental migration [Conde, 2008, Lam and Yeoh, 2019]. Therefore, migration decisions incur a tradeoff between parental time and monetary investments into a child, two fundamental inputs determining a child's development and educational outcomes. When these inputs are given and in what amounts can be important for child development [Cunha and Heckman, 2008, Cunha et al., 2010]. The importance of these inputs might vary by the age of the child as well as whether the mother or the father chooses to migrate. Therefore, who chooses to migrate and when potentially has significant welfare implications for children left behind. Such considerations, in turn, can affect the parental decisions to migrate in the future.

This paper pursues three research objectives that build upon one another. The first is to understand how the interaction and relative importance of parental time and monetary investments on a child's educational outcomes vary between younger and older children. The second is to provide insight into how parental migration decisions are impacted by the needs of their children within a dynamic framework, accounting for the evolving requirements of parental time and monetary inputs over the course of a child's formative years. Finally, I evaluate the net impact of temporary labour migration on the educational outcomes of children. I will now provide an overview of my research approach and follow this with a preview of the results obtained while simultaneously connecting these to the literature that I have built upon in this paper.

To pursue the three research objectives, I estimate a dynamic model of migrant households with an embedded age-specific child education production function by conducting a seven-year panel survey of 1100 Filipino migrant families and combining it with newly assembled administrative data from the Philippines Department of Education and the Department of Migrant Workers. Parents in the model make repeated migration decisions and obtain direct utility from consumption and the academic performance of their children. The age-specific education production functions determine the academic outcomes of the children given the endogenous parental choices of time and monetary investments made each period and the starting level of the child's human capital, which is determined by parental investments from the previous period. Flexibility in the assumed specification of the education production function permits me to explore how the relative importance and degree of substitutability or complementarity between inputs may change as the child matures over time. This provides a framework for understanding the tradeoff that is incurred between parental time investments and monetary resources when mothers and fathers are choosing whether to migrate or not in order to earn a considerably higher foreign wage, and how parents will internalize the effects of their migration on their children, which in turn affects their future migration decisions.

Estimation of the model can be broken down into three parts, estimation of the education production function, estimation of the parental migration decision rules, and estimation of the parental preferences in the household model. Estimation of the education production functions is made possible with the substantial variation in the timing of parental time inputs and monetary investments in the data that arises from the systematic and widespread international migration of Overseas Filipino Workers (OFWs) in my new dataset. A key challenge of human capital production function estimation is the identification of endogenously selected parental inputs [Attanasio et al., 2021, Cunha et al., 2010, Cunha and Heckman, 2008, Todd and Wolpin, 2007, 2003]. To combat this endogeneity, I exploit shocks to the demand for male and female Filipino migrant workers in East Asia and the Middle East. The empirical strategy used to estimate the education production function is not dependent on the beliefs or preferences of the parents within the household, particularly regarding the properties of the education production function.

Nevertheless, the parental migration decision rules derived from the model are a function of the estimated education production function, especially the child's initial endowments which are unobservable to the econometrician. The panel structure of my dataset allows me to model the child's education production function with the endowments of each child as a child-fixed effect that enters as a separate input and may enhance the productivity of other inputs. This is a variable that has been subsumed into the child's starting level of human capital each period in the literature so far [Attanasio et al., 2021]. I utilize a latent measure model to estimate the child's endowment after having estimated the child's education production function. As the child's endowment is a state variable that enters into the parent's migration decision rule derived from the model, I may only estimate this decision rule after I have estimated each child's endowment. The estimates of the parental migration decision rule offer insights into how migrants make repeated migration decisions as they internalize the evolving needs of their children. Moreover, they shed light on the parental beliefs and knowledge of the properties of the child's education production function. I finally impose further structure onto the model and estimate the household's preference parameters to run counterfactual simulations and calculate the net impact of migration.

Under all specifications of the age-specific child education production function, I find monetary resources play a more significant role in shaping child human capital from the ages of 11–15. Conversely, both maternal and paternal time inputs are more critical between the ages of 6–10 even after accounting for the educational attainment of the parent. A mother's time is always significantly more productive in generating human capital compared to the father's time, even after controlling for the age of the child and the educational attainment of the parents. Educational attainment of the parents is important for the productivity of parental time inputs when the child is young, but its importance diminishes as the child matures. These findings contribute to the existing body of work on child human capital production function estimation by separately identifying the importance of maternal and paternal time inputs and understanding the role educational attainment of the parents has in determining the productivity of time inputs.[2]

Under the preferred triple nested constant elasticity of substitution (CES) specification of the child education production function, I additionally find that the elasticity of substitution between time inputs and educational expenditures increases from 0.20 to 0.46 when the child matures from the ages of 6–10 to the ages of 11–15. This suggests there is a persistent complementarity between time inputs and educational expenditures that

[2] See Caucutt et al. [2022], Agostinelli and Sorrenti [2022], Attanasio et al. [2020a]

weakens as the child matures. The elasticity of substitution between time inputs from the mother, father, and grandparents, increases from 0.20 to 3.00 as the child progresses from the ages of 6–10 to the ages of 11–15. This implies that time inputs from key caregivers when the child is young are complementary. However, as the child matures and the relative importance of time inputs diminishes, the time inputs particularly from the mother and father become good substitutes for one another. These findings advance the insights into the literature that estimates the substitutability and complementarity of inputs in human capital production functions. My findings of strong complementarity between current inputs, particularly when the child is young, align with prior findings. Additionally, my newly collected dataset allows me to relax the dependence structure between lagged academic outcomes, parental educational attainment, and the unobserved idiosyncratic shock of the child. Consequently, I use weaker exogeneity assumptions than the ones used by previous authors.[3]

From the estimated migration decision rule, I find that when parents know their children possess a greater endowment of abilities that enhances their academic outcomes, they will more likely migrate. Similarly, when parents observe their children to be doing well academically, parents tend to migrate more. This suggests that parents internalize the effects of their absence on their children when choosing whether to migrate and only migrate more when they have confidence in their children's academic success and believe their presence is less essential. My estimates also reveal that parents are inclined to migrate between 12–24 days more per year for each year the average age of their children increases. This behavior of migrating more when the children are older aligns with the notion that parents are indeed knowledgeable of the evolving requirements of parental time and monetary inputs into a child and the tradeoffs of migrating and having greater earnings potential abroad. However, the postponement of increased migration must be balanced with the immediate needs of household consumption and the alluring foreign wages and job opportunities. Specifically, when a mother experiences an upsurge in the number of relevant foreign work contracts and corresponding wages in these contracts, her time spent abroad will increase, while the father's time spent abroad will decrease, and vice versa. The observed phenomenon could be explained by the desire to avoid further separation disutility and the adverse impacts of additional parental absence on a child's educational outcomes. Therefore, given a relative increase in the returns of migrating for a parent that draws him or her abroad, the other parent will preferably remain at home. Together, these findings offer new insights into how the changing welfare of children, impacted by parental migration choices, will, in turn, shape parental migration decisions within a single dynamic framework that incorporates previously studied drivers of migration. In doing so, this advances the existing literature that has focused exclusively on the barriers, risks, and costs of migration and the potential monetary gains of migration within a static setting, which are well-studied determinants of international temporary migration and domestic temporary seasonal migration decisions.[4]

Performing an accounting exercise utilizing the estimates of the child education production function, I calculate a range for the net impact of temporary migration conditional on; (i) the age of the child, (ii) the education level of the migrant parent, and (iii) the gender of the parent. When children are aged 6–10,

[3]See Agostinelli and Wiswall [2023], Caucutt et al. [2022], Attanasio et al. [2020b, 2017, 2021]

[4]See [Bryan and Morten, 2019, Borjas et al., 2018, McKenzie and Yang, 2015, Bryan et al., 2014, McKenzie et al., 2014, Gibson and McKenzie, 2011, Yang, 2008, Munshi, 2003]

mothers and fathers whose highest educational attainment is secondary school education and also work in a low skilled occupation, such as domestic work or manual construction, will have a net negative impact on educational outcomes. For example, a mother who is a domestic worker with only secondary school education is predicted to decrease their children's test scores by at least 0.045 standard deviations relative to all children in the Philippines of the same age for every month they are abroad and working. Nevertheless, it is possible for a mother or father with a completed tertiary education who also works in a high skilled occupation, such as nursing or mechanical engineering, to have a positive net benefit on their children upon migrating. For example, a mother with tertiary education who is a nurse could potentially increase their children's test scores by up to 0.008 standard deviations for every month they are abroad. However, this potential increase is an upper bound and there is a far greater likelihood of the parent's migration being detrimental to the child when the child is 6–10 as parental time inputs are far more critical. Conversely, when children are aged 11–15, my calculations suggest that the migration of mothers and fathers can always have a net positive impact on their children's educational outcomes. This result is unsurprising as the productivity of parental time inputs falls substantially while the importance of educational expenditures increases as the child matures. These calculations are complemented by counterfactual simulations that shut down migration in various ways. The results of these counterfactual simulations will be reported and updated here upon finalizing the estimation of the migrant household's dynamic optimization problem.

Previous studies that have studied the net impacts of temporary migration on the educational outcomes of left-behind children have studied this question in a static setting and primarily reported the aggregate impacts of migration on children.[5]. As the impacts of temporary migration are highly dependent on the timing due to the evolving requirements of parental time and monetary inputs over the course of a child's lifetime, I investigate this question in a dynamic framework that quantifies the importance of each mechanism through which temporary migration impacts the educational outcomes of children. Therefore, a principal contribution of this paper is the ability to distinguish and quantify the impacts of both maternal and paternal migration as well as increased expenditures as a result of increased household income through remittances within a single dynamic framework. More broadly, these results enrich the literature concerning the welfare consequences of international temporary migration and domestic temporary seasonal migration. Previous analyses have predominantly focused on remittances, household income, benefits of risk sharing, and informal insurance within a static setting, with relatively limited attention given to children's outcomes.[6]

The paper proceeds as follows. Section 2 describes the Filipino migration context and institutional setting governing the migration of OFWs. Section 3 discusses the data collection methodology and resulting data set I collected for this paper. Section 4 presents the theoretical framework, identification, and estimation of the child's education production function. Section 5 presents the estimates from the child education production function, the net impacts of migration on the educational outcomes of children, and the migration decision rule and educational expenditure allocation decision rule. Section 6 discusses the estimation of the migrant household's optimization problem with counterfactual analysis to come soon. Section 7 concludes.

[5]See [Zhang et al., 2014, Chen, 2013, Antman, 2012, 2011, McKenzie and Rapoport, 2011, Edwards and Ureta, 2003]

[6]See [Mobarak et al., 2023, Lagakos et al., 2023, Meghir et al., 2020, Khanna et al., 2022, Morten, 2019, Theoharides and Yang, 2018, McKenzie and Yang, 2015, Bryan et al., 2014]

The Filipino Migration Context

2.1 Government Agencies:

Overseas Filipino Workers (OFWs) constitute one of the largest overseas working populations in the world, with cash remittances from OFWs accounting for almost 10% of the Philippines' GDP. To protect this population of workers the Overseas Workers Welfare Administration (OWWA) was established in 1977 with the primary purpose of protecting the interests and welfare of OFWs and their families left behind. This was further supplemented with the establishment of the Philippine Overseas Employment Administration (POEA) in 1982, an agency that helped with the promotion and regulation of recruiting OFWs to ensure their safety abroad. Under the rules and regulations of the POEA, all OFWs are legally required to register with the POEA and obtain an Overseas Employment Certificate (OEC) that must be presented to an immigration officer when departing from the airport. In February 2022, the Department of Migrant Workers was founded and absorbed the POEA and OWWA. The DMW now functions as the executive department of the Philippine government responsible for protecting the rights and promoting the welfare of OFWs and their families.

To protect the rights of OFWs, a key function of the DMW is to set laws, regulations, and negotiate bilateral agreements between the governing bodies of the Philippines and popular migration destinations regarding the working rights and contract terms for OFWs.[7] In particular, the minimum wage amounts, compulsory holidays, safeguards for contract violation, and other key components of working contracts are often stipulated. The bindingness of these laws and regulations is reflected in the historical oversupply of OFWs relative to the demand for OFWs by employers abroad particularly with non-professional degree occupations that do not require a full bachelor's degree [McKenzie et al., 2014, Yang, 2008]. This is important as it implies that the overwhelming majority of OFWs do not have the ability to negotiate the terms of the contracts and in particular the wages of their contracts. Variations in the take-home wage for a migrant primarily arise from the variation in the recruitment agency fees that must be paid.

2.2 Recruitment Agencies & Migration Networks:

To assist and regulate the matching of OFWs with prospective overseas employers, a sophisticated network of "recruitment agencies" is used. A recruitment agency is an officially licensed agency that is vetted rigorously by the POEA. A typical recruitment agency will have offices in a specialized migration destination as well as corresponding satellite offices in the Philippines. Any overseas employer that wishes to employ an OFW must first submit a work contract, more formally known as a "job order", to the overseas office of a licensed recruitment agency. Only once this contract is vetted and verified by the Philippines Overseas Labour Office (POLO) and subsequently the POEA, will this contract then be made available to OFWs by the recruitment agency in the Philippines. The recruitment agency then matches suitable applicants with the contract's requirements and acts as a mediator to facilitate job interviews between the employer and prospective OFW applicants. The overseas employer will then select their favored applicant and the recruitment agency will then be responsible for processing all of the remaining paperwork to ensure that the OFW may travel abroad

[7] Previously the POEA was the primary agency that performed this function.

for their employment opportunity.

In many migration contexts, migration networks between a migration destination and a migrant's origin are often formed informally and serve to lower the cost of migration, increase the payoffs and benefits of migrating, and reduce the risk that is associated with migrating [Morten, 2019, Munshi and Rosenzweig, 2016, Munshi, 2003]. In the Filipino migration context, because the migration process is highly regulated and formalized through recruitment agencies these informal migration networks and connections are dominated by more formal networks created by the recruitment agencies. This more formal migrant origin-destination network arises because recruitment agencies will usually specialize and cater to specific occupation categories in a specific migration destination and have corresponding satellite offices in distinct locations in the Philippines. Moreover, recruitment agencies within a local area will often agglomerate and service very similar migration destinations that are all within the same global region. For example, recruitment agencies in the Bangsamoro Autonomous Region in Muslim Mindanao (BARMM) region of the Philippines are particularly well known for supplying OFWs to the Middle East. A prospective migrant's choice of migration destinations is therefore limited to the migration destinations serviced by their local recruitment agencies unless the migrant wishes to incur significant additional costs and apply for jobs through recruitment agencies outside of their set of local recruitment agencies.

This notion is supported by evidence from the multitude of focus group discussions conducted prior to data collection. In these discussions, an overwhelming majority of interviewed OFWs mentioned that they often do not have a strong preference regarding the migration destination. Their preference for the migration destination is third order relative to (1) the ability to work for a higher wage abroad and, (2) guaranteed stable long-term employment. This is a consequence of the inherent lack of stable work within the Filipino economy especially among middle to low-skill workers and non-professional degree occupations. Short-term contractual work in the Philippines represents between 27-45% of total employment in the Philippines, depending on the measure of "contractual work" [Tolentino, 2017, Bersales, 2016].[8]

2.3 OFW's Maintaining Contact With Family

The Philippines was globally number one in terms of social media usage for the sixth year in a row in 2021, with a huge majority of this time being spent on Facebook. Facebook Messenger reigns as the predominant means of communication among Filipinos, with over 90% usage among those with internet access. Notably, it stands out because messaging through Facebook Messenger doesn't consume prepaid mobile data [Chua, 2021, Malig, 2021]. This platform is particularly integral to migrants, virtually serving as the universal choice for OFWs to maintain contact with their families. Due to the deep entrenchment of Facebook usage the OWWA, POEA, and major OFW news and media outlets disseminate important messages and information primarily through Facebook and Facebook Messenger through their social media platforms.

[8] The lower estimate of 25% arises from only looking at non-regular workers in establishments with 20 or more workers. The higher estimate includes non-regular and contractual workers who work in micro and small establishments.

Data Collection

Data collection can be broken down into primary and secondary data collection. Primary data collection constituted of collecting a retrospective panel of data from 2015–2022 on a sample of 1100 migrant families that contained a total of 2904 children via phone survey. Data from the pilot and focus group discussions strongly suggested data quality sharply drops prior to 2015. Due to the retrospective nature of the panel data, the population of interest for this study was all Filipino households with at least one parent who migrated since 2015 and had at least one child between the ages of 9 and 16 at the time of the survey. Secondary data collection comprised of collecting administrative data from three key sources. The first was the Philippines Department of Education (DepEd) where I collected administrative data on the academic outcomes of children, which was then linked to the primary data. Secondly, I collected panels of administrative data from 2010–2022 on all job contracts offered to OFWs and all successfully deployed OFWs from the Department of Migrant Workers (DMW) and the Philippines Overseas Employment Administration (POEA). This data was used to critical to the construction of the instrumental variables discussed below.

3.1 Primary Data Collection:

Primary data collection can be broken into three stages:

1. Creation of Sample Frame: Overseas Filipino Workers (OFWs) took a 5-10 minute self-administered survey conducted via a Facebook Messenger (Facebook Messenger) Chatbot.
2. Migrant Phone Survey: A 45 - 60 minute phone survey conducted with the primary migrant of the household (71% response rate)
3. Migrant Household Phone Survey: A 45 - 60 minute phone survey conducted with the household head (83% response rate)

3.1.1 Creation of Sample Frame:

Due to data privacy laws in the Philippines, I was not able to use the databases of the OWWA and POEA as a sample frame to contact and recruit migrants into my phone survey. Instead, I had to create my own sample frame by gathering basic information, consent, and contact information on a representative sample of all OFWs and subsequently filter and recruit eligible migrants into the survey.

The sample frame I use for my phone surveys is designed to represent the entire population of OFWs. Given the Filipino migration context, I make the assumption that a representative sample of all OFWs, both those currently overseas and those in the Philippines, can be obtained from the following three groups. (1) OFWs who currently follow the official social pages of POEA, OWWA, and major OFW news and media on Facebook. (2) OFWs recorded in the databases of OWWA and POEA. (3) OFWs who are either departing from or returning to the Philippines through the airport. To create this sample frame, I gather data on OFWs and their families by utilizing a brief 5-minute self-administered Facebook Messenger chatbot hosted by the company Chatfuel. To encourage survey participation in this initial self-administered survey, the communications team at the International Labour Organization (ILO) and the International Organization of Migration (IOM) collaborated closely with me. Together we developed branded promotional materials, which were subsequently distributed by the following means:[9]

1. Official social media teams of OWWA, POEA, and major OFW news and media outlets regularly shared the promotional material across their available social media platforms.
2. The Philippines Overseas Labour Offices (POLOs) situated in each major OFW migration destination regularly posted promotional material on their respective social media channels.
3. Text messages containing the promotional material were sent via text messenger blasts to all migrants listed in the OWWA and POEA databases.
4. Physical distribution of promotional material by POEA, which was attached to the cover of the OFW handbook, a guide provided to departing OFWs at five out of the eight international airports.
5. The POEA distributed promotional materials to departing migrants by affixing them to the cover of the OFW handbook, a handbook given to all departing OFWs across major international airports nationwide. Tarpaulins displaying the same promotional material with a scannable QR code to access the online Chatfuel survey were also permanently installed at these locations.
6. OWWA physically distributed promotional material to returning migrants while they awaited transport to hotel quarantine facilities. Tarpaulins with the same promotional content were set up at major airport bus terminals.

The sample frame therefore consists of all OFWs who responded to this promotional material, completed the self-administered Facebook Messenger survey, and consented to being contacted for a follow-up phone survey. The characteristics of the OFWs from this sample frame are compared to the basic characteristics of the entire population of OFWs given by the DMW's administrative dataset on all successfully deployed OFWs in columns one and two of table 1 below.

Table 1: Administrative Data vs. Primary Data Collected

	DMW Admin Data	Enlistment Survey Respondents	Respondents w/ Children	Mig Ph Survey Respondents
% Males	41%	28%	27%	21%
% Females	59%	72%	73%	79%
Avg Age	34	38	39	38
Avg Yrs of Edu	11.81	10.73	10.49	9.90
Avg Yrs Abroad	2.91	2.80	4.90	5.23
Avg No. of Children	N/A	1.12	2.83	3.62
No. of Obs	3,722,364	31,468	12,565	1,100

[9] For examples of the promotional material, please refer to appendix E.

3.1.2 Migrant & Household Phone Survey:

From the incoming flow of all OFWs that make up the sample frame, eligible migrants and their families were filtered out and randomly drawn to participate in the phone surveys. Among those migrants randomly drawn into the phone survey, 71% of these migrants responded and completed the 45-60 minute migrant phone survey. Upon the completion of the migrant phone survey, the same enumerator was tasked to conduct the corresponding 45-60 minute phone survey with the migrant's household, for which there was an 83% phone survey completion rate. The migrant phone survey gathered detailed data concerning the employment history of the primary migrant in the household. This encompassed a wide range of information such as wages, occupation, days and hours worked, costs to migration, migration destination, and remittances. Simultaneously, the household phone survey systematically gathered comprehensive information on child-related and general household expenditures, savings, investments, assets, liabilities, the health status of household members, and the employment histories of household members. The latter also included information on the monthly location of each household member throughout the retrospective panel.

3.2 Secondary Data Collection:

Secondary data collection revolved around the collection of administrative data from two main sources: (1) Philippines Department of Education (DepEd), (2) Department of Migrant Workers (DMW)

3.2.1 DepEd Administrative Data Collection

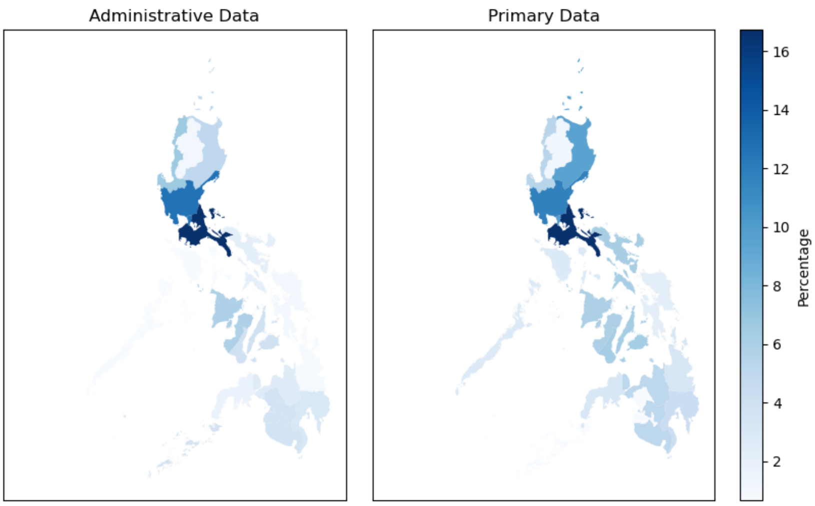
Starting in 2019, I collaborated with the Philippines Country Office of the Innovations for Poverty Action (IPA) to secure an unprecedented data-sharing agreement (DSA) with the DepEd. This DSA granted unrestricted access to de-identified administrative data on every student who ever enrolled in school in the Philippines. This access enabled me to link the administrative data concerning a child's academic progress to the data collected on the migrant and the migrant's household, allowing me to track and measure the academic performance of children over time. To ensure the measure of academic performance remains consistent across time regardless of the child's age and the variations that may arise from attending different schools, I assembled a panel of data from two primary sources: (1) The Learner Information System (LIS), (2) The Bureau of Education Assessment (BEA). Utilizing data from these two sources, I construct an age-standardized test score, using the population of all enrolled students of the same age in the Philippines as the reference group for standardization. For specific details on the administrative data collected and the construction of the outcome variables used for estimation please refer to appendix A.

Out of the 2,904 biological children within the 1,100 migrant families, a total of 2,412 children fell into one of two categories: they were either over the age of five and had commenced their schooling at some point before 2022, or they were young enough such that they were enrolled in school in 2014. Of the 2,412 children, the DepEd was able to successfully match 94% of them with their corresponding administrative academic records.

3.2.2 DMW Administrative Data Collection

Due to the role of the DMW in the Filipino migration context, the DMW has extensive data on every approved overseas job order that is made available to OFWs. The administrative database that houses these job orders, provides detailed information on the terms of the contract that a migrant will work under while abroad. This encompasses information such as the migration destination, wages, contract length, occupation, deployment date, skills required, etc. In addition, I also receive supplementary information on the characteristics of each OFW who accepts a given job order and is successfully deployed. This includes information on the migrant's age, gender, educational level (from 2018 onwards), and their place of origin in the Philippines. With assistance from the ILO and IOM, the DMW and POEA shared a month-by-month panel of approved job orders and successfully deployed migrants from January 2010 until June 2022. Figure 1 below presents a comparison between the migrant household locations of all successfully deployed migrants in the administrative dataset to the migrants in my sample who completed both phone surveys.

Figure 1: Migrant Household Locations



Theoretical Framework

Parents in the model make repeated migration decisions and obtain direct utility from consumption and the academic performance of their children, which is dictated by an age specific child education production function. This provides a framework for parents to trade off parental time and monetary resources into their children when choosing whether to migrate or not in order to earn a considerably higher foreign wage. For the purposes of exposition and clarity to the reader, I discuss the model with only three periods and one child in the household. This is sufficient in providing intuition and understanding of the mechanics behind the decisions being made. This model provides motivation for the instruments used in the first stage regressions of the endogenous inputs in the child's education production function. Dynamic decision rules that parents make regarding parental migration and educational expenditure allocation across children in the household are also derived as a function of the state variables each period. The estimation of these decision rules offer insights into how migrants make repeated migration decisions as they internalize the evolving needs of their children. I finally impose further structure onto the model and estimate the household's preference parameters to run counterfactual simulations and calculate the net impact of migration. The extension of this model to households with multiple children and its adaptation to the dataset for the purpose of estimating the parameters in the household's maximization problem is described in detail in appendix D.

4.1 Model of the Migrant Household

4.1.1 The Child Education Production Function

The migrant household begins in period one when their child is between the ages of 6 - 10. This household is endowed with initial assets A_0. The child enters the model with a set of initial endowments, Λ, and an initial test score when starting school S_0. A suggested interpretation of Λ is the endowment of the child's innate abilities and preferences, which is known by the parents but unobserved by the econometrician. It also encapsulates the accumulated stock of all past unobserved parental investments and human capital of the child prior to the child's first observed academic test score and parental investments in the data. The child's education production function h_1 governs the evolution of the child's test score from the initial observed test score S_0 to the final academic outcome S_1 in period one that parents will receive utility from. Inputs into this production function are time from the mother (T_{m1}), father (T_{f1}), and grandparents (T_{g1}), educational expenditures in period one (E_1), and the initial observed test score S_0. This is written formally as:

$$S_1 := h_1\left(S_0, T_{m1}, T_{p1}, E_1; T_{g1}, \text{Edu}_m, \text{Edu}_f, \Lambda, \varepsilon_1\right). \tag{1}$$

I assume Edu_m and Edu_f, the educational attainment of the mother and father, are determined prior to the start of the model. ε_1 is an unexpected idiosyncratic shock to the child. In period two, the child matures from the age range of 6 - 10 to the age range of 11 - 15. The child's corresponding education production function is denoted by h_2. The inputs into h_2 are the analogous time and educational expenditures put into the child in period two as well as the child's starting test score in period two (S_1), which was endogenously determined by parental investment decisions made by the parents in period one and S_0. That is;

$$S_2 := h_2\left(S_1, T_{m2}, T_{p2}, E_2; T_{g2}, \text{Edu}_m, \text{Edu}_f, \Lambda, \varepsilon_2\right). \tag{2}$$

The production function h_2 is permitted to be different from h_1 as the amount and type of parental investments needed by children may differ by age. With the focus of this paper being from the ages of 6–15, the existence of period three in this model is to provide incentives for the household to continue investing in the children's education and also continue saving so that we may study the behavior of migrant households in periods one and two. The child education production function in h_3 is therefore assumed to be the identity function with respect to S_2. That is;

$$S_3 := h_3\left(S_2, T_{m3}, T_{p3}, E_3; T_{g3}, \text{Edu}_m, \text{Edu}_f, \Lambda, \varepsilon_3\right) \equiv S_2 \tag{3}$$

4.1.2 The Migration Decision:

Let $\mathcal{D}$ be the set of the top 40 migration destinations for all OFWs and $\tau_{mt}, \tau_{ft} \in \{0, 1\}$ be the mother and father's respective endogenous choice of whether to migrate away for work or not in period t. Specifically, I assume $\tau_{mt}, \tau_{ft} = 1$ if the mother or father chooses to migrate, and 0 if they choose not to migrate. Given the institutional setting described above in section 2.1 I further define the observed/realized parental time at home in a given period by $T_{mt}, T_{ft} \in [0,1]$ where:

$$T_{mt} = 1 - \underbrace{\frac{\delta_m + \zeta_{mt}}{\sum_{d \in \mathcal{D}} N_{\ell d} Q_{mdt}}}_{\text{Waiting Time}} \tau_{mt}. \tag{4}$$

Definition 4.1.1. *The variable Q_{mdt} is defined to be the total number of foreign contracts at time t from destination d specific to the primary occupation of the mother in the household multiplied by the fraction of successfully deployed female OFW's in this occupation to destination d at time t.*[10]

Definition 4.1.2. *The variable $N_{\ell d}$ denotes the historic migration network from the households location ℓ to migration destination d defined by:*[11]

$$N_{\ell d} := \frac{\text{Number of migrants from } \ell \text{ to } d \text{ from 2010 - 2013}}{\text{Total number of migrants from } \ell \text{ from 2010 - 2013}}. \tag{5}$$

The waiting time in eq. (4) is a function of the relevant foreign job opportunities available to the mother at time t from each destination d, weighted by the migration networks between her home municipality ℓ and d. Therefore, only exogenous shifts in the number of contracts from migration destinations where the migrant has a strong network connection through the local recruitment agencies will be likely to impact the waiting time. Conversely, exogenous fluctuations in the number of relevant job opportunities from migration destinations where the migrant does not have a strong network connection will be unlikely to have any impact on the waiting time. As the number of relevant job openings increases, the waiting time will decrease and the migrant will be more likely to be deployed sooner. The respective change in the waiting time in period t given a change in the number of relevant job openings in period t is governed by the parameter δ_m and the time-specific idiosyncratic shock ζ_{mt} experienced by the mother. An analogous expression for the father defines T_{ft} with the corresponding variables Q_{fdt}, the parameter δ_f, and the idiosyncratic shock ζ_{ft}.

If the mother chooses to migrate abroad at time t she will earn wage $Y_{m,\text{mig}}$, which I assume to be always strictly higher than the wage she may earn at home, $Y_{m,\text{home}}$. A similar assumption is made for the father.

Definition 4.1.3. *The variable Y_{mt} (Y_{ft}) denotes the total income for the mother (father) in period t, i.e.*

$$Y_{mt} := T_{mt} Y_{mt,\text{home}} + (1 - T_{mt}) Y_{mt,\text{mig}} \qquad \text{and} \qquad Y_{ft} := T_{ft} Y_{ft,\text{home}} + (1 - T_{ft}) Y_{ft,\text{mig}}. \tag{6}$$

Migrating away therefore allows the household to increase total income in the household, which can potentially increase consumption C_t and expenditures made into their child E_t. However, they will incur migration costs K_{mt} and K_{ft} and parental absence will decrease the time inputs of the mother and father, T_{mt} and T_{ft}, which are critical inputs into the child's education production function.

[10] If an individual is observed to work in two or more occupations during the panel, their primary occupation is defined to be the occupation in which the individual worked in for the longest during this panel.

[11] ℓ is defined at the municipality level as per the Philippines Standard Geographic Code, a systematic classification and coding of geographic areas in the Philippines defined by the Philippines Statistic Authority.

4.1.3 The Household's Maximization Problem:

Each period the household receives utility from consumption and how well their children do at school. The household will incur separation disutility whenever the mother or father migrates and spends time away from the household, hence the direct inclusion of T_{mt} and T_{ft} in the utility function below. I assume that parents cooperate and act in the best interests of the household and their children and therefore interact within a unitary household. The endogenous choices the parents must make each period are the amount to consume, the amount to save or borrow (A_t), the amount to spend on the child's education, and whether or not each parent will migrate away from the household for work. Formally the household's maximization problem can be written as:

$$\max_{\substack{C_1,\tau_{m1},\tau_{f1},E_1,A_1\\ C_2,\tau_{m2},\tau_{f2},E_2,A_2\\ C_3,\tau_{m3},\tau_{f3},E_3,A_3}} \left\{ \begin{array}{c} U\left(C_1, T_{m1}, T_{f1}; S_1\right) + \beta\mathbb{E}\left[U\left(C_2, T_{m2}, T_{f2}; S_2, \right)\right] \\ +\beta^2\mathbb{E}\left[U\left(C_3, T_{m3}, T_{f3}; S_3\right)\right] \end{array} \right\} \tag{7}$$

subject to:

1. The per period budget constraint for period $t = 1, 2$ and 3:

$$C_t + E_t + K_{mt}\tau_{mt} + K_{ft}\tau_{ft} + \frac{A_t}{R} \leq Y_{mt} + Y_{ft} + A_{t-1} \tag{8}$$

2. The child's education production function in period $t = 1, 2$, and 3:

$$S_t := h_t\left(S_{t-1}, T_{mt}, T_{pt}, E_t; T_{gt}, \mathrm{Edu}_m, \mathrm{Edu}_f, \Lambda, \varepsilon_t\right). \tag{9}$$

3. The equations determining the realized parental time at home in period $t = 1, 2$, and 3 for the mother and father:

$$T_{mt} = 1 - \frac{\delta_m + \zeta_{mt}}{\sum_{d\in\mathcal{D}} N_{\ell d} Q_{mdt}}\tau_{mt} \tag{10}$$

and

$$T_{ft} = 1 - \frac{\delta_f + \zeta_{ft}}{\sum_{d\in\mathcal{D}} N_{\ell d} Q_{fdt}}\tau_{ft}. \tag{11}$$

4. Expenditures on the children can never be negative, for all periods $t = 1, 2$, and 3:

$$E_t \geq 0. \tag{12}$$

4.1.4 Uncertainty in the Model:

This model assumes that the parents face two types of uncertainty that they must take expectations over when making decisions for periods two and three. The first type of uncertainty arises from the child's idiosyncratic shock ε_t to their academic outcomes. The second type of uncertainty arises from the idiosyncratic shock to the migrant's waiting time ζ_{mt} and ζ_{ft} respectively. I assume that parents are completely myopic with respect to the uncertain future wages in the model when making their inter-temporal labor force participation decisions and whether to migrate or not. To justify this modeling choice, I show the inclusion of realized future wages as an exogenous state variable and right-hand side regressor when estimating the parental migration decision rules do not change the other estimated coefficients significantly.[12] This suggests that even if future wages were to be an important factor in determining parental migration decisions, its omission will not affect our understanding of the importance of other factors to parental migration decisions that this paper focuses on.

[12]Please refer to table 17 in appendix B, which shows the estimates of the migration decision rule derived from the model with the inclusion of realized future wages as an exogenous state variable and right-hand side regressor. This table should be compared with table 12, which estimates the same migration decision rule without the inclusion of the future wages.

4.1.5 Dynamic Decision Rules & Instruments:

By construction of the model, the exogenous state variables each period are the parental wages at home and abroad $Y_{mt,\text{home}}, Y_{mt,\text{mig}}, Y_{ft,\text{home}}, Y_{ft,\text{mig}}$, the number of occupation specific foreign contracts $\{Q_{mdt}, Q_{fdt}\}_{d\in\mathcal{D}}$, the historic networks $\{N_{\ell d}\}_{d\in\mathcal{D}}$, migration costs K_{mt}, K_{ft}, the child's endowments Λ, the parents educational attainment $\text{Edu}_m, \text{Edu}_f$, the interest rate R, the discount rate β, and the age of the children in the household each time period. Exogeneity of the state variables in this context is with respect to the household's maximization problem. They are determined outside of the model or prior to the start of period one.[13] The endogenously determined state variables of the model that are determined at the beginning of each period by the previous periods choices are the lagged educational outcomes of each child S_{t-1} and the assets and savings A_t. I now discuss two decision rules derived from model, which will be subsequently estimated below.

The dynamic decision rules derived from this model each period must therefore be a function of these exogenous and endogeneous state variables. The two key dynamic decision rules of interest derived from this model are the parents migration decision rule, and the expenditure allocation decision rule across children. The decision rule for parental migration internalizes the impacts of parental migration on their children's educational outcomes through the endogenous state variable S_{t-1}, which is effected by prior migration, and the age of the children as the relative productivity of inputs may differ across the different periods as the child matures given the parameters in the education production function h_1 and h_2. The parents also take into account the child's endowments, Λ, which can boost the marginal productivity of inputs. Thus, it is clear from the model that the responses of the dynamic parental migration decision rule to the changes in the state variables that characterize a child's state at the beginning of a period will be highly dependent on the the estimated parameters from the age specific education production function. The decision rule for parental migration derived from this model also encapsulates the already well-studied drivers to migration such as foreign wages and the number of relevant employment opportunities abroad, which shift the monetary returns to migration.

In a similar manner, the decision rule for expenditures made for each child also internalizes the impacts of parental migration on their children's educational outcomes through S_{t-1} and the age of the children. Parents also account for the importance of the child's endowments in determining the productivity of their choice of educational expenditures. Moreover, educational expenditures are a function of the exogenous state variables that shift the monetary returns to migration. The capacity for migrant parents to allocate additional monetary resources to their children is a function of their ability to earn higher foreign wages. Therefore, the subset of exogenous state variables that shift monetary returns to migration is used to instrument the two key endogenous inputs in the child's education production function: (1) Parental time inputs, which are a direct function of the parent's migration decision. (2) The educational expenditures for each child.

[13] Although parental education is an endogenous choice made by the parents, I assume that this endogenous choice is made prior to the beginning of period one and does not change throughout the model. This reflects an empirical finding from my dataset, whereby none of the parents in my sample raised their educational attainment levels throughout the panel. Nevertheless, when estimating the child's education production function, I account for the possible endogeneity of the parent's educational attainment. This is discussed in detail below.

4.2 Identification of the Production Function:

I now provide a detailed description and justification of the instrumental variables used for parental investments of time and educational expenditures into the child. In what follows, the descriptions are for a fixed and arbitrary household i and the mother and father in household i. As household i may have multiple children, I abuse notation and use $j \equiv j_i$ to denote child j_i in household i.

To estimate a child's education production function (h) that is embedded into the household's i's maximization problem, I first assume that we have additive separability of the child's fixed effects and the child's idiosyncratic error term. Thus, we estimate the following general functional form:

$$S_{ijt} := h\left(S_{ijt-1}, T_{imt}, T_{ift}, E_{ijt}; T_{igt}, \mathrm{Edu}_{im}, \mathrm{Edu}_{if}\right) + \Lambda_{ij} + \varepsilon_{ijt}. \tag{13}$$

The econometrician must account for the endogeneity between the parental inputs and the unobservables denoted by Λ_{ij} and ε_{ijt}. The key endogenous choice variables from the household's optimization problem that enter as inputs into the child's education production function of concern are parental time and monetary investments into education. I also treat the child's lagged test score and the education levels of the parents as endogenous. This relaxes two key assumptions of exogeneity that have been made in prior literature on the estimation of child education production functions. As the primary focus of this paper is on parental migration and time investments, I assume that the presence or absence of grandparents $T_{igt} \in \{0, 1\}$ in a household is exogenous. A more detailed justification of this assumption with empirical evidence is given in section 4.2.4. These key endogenous inputs of interest, their corresponding data source, and the exogenous state variables from the model that motivate the instruments used to identify these endogenous inputs are summarized in table 2. A more in-depth description of the instruments and strategy used to identify the endogenous inputs is given momentarily.

Identification of the production function is plagued by three sources of endogeneity that are summarized in table 3. The first source of endogeneity arises from potential measurement error in the data, which is specific to the context of this paper due to the retrospective nature of the data gathered. The second source of endogeneity arises from time-varying shocks that occur to the household or child that influence the endogenous choice of time and monetary investments a parent will make into the child. An example of this is an unexpected negative health shock the child may experience. The third source of endogeneity arises from time-invariant unobservables such as unobserved innate ability or endowments of a child. To exploit the time series nature of the panel data I collected, I include Λ_{ij}. This absorbs the time-invariant endogeneity resulting in the idiosyncratic shock ε_{ijt} in eq. (13) to consist of only the first two sources of endogeneity. However, the addition of Λ_{ij} introduces Nickell bias over and above other biases that arise due to the regressors not being orthogonal to ε_{ijt}, especially with the inclusion of S_{ijt-1} [Nickell, 1981]. To accurately estimate h and combat this endogeneity I utilize a panel of external instruments.

The instruments for parental time and monetary investments must be strong predictors of the number of months that each parent is physically present in the household and the amount of monetary expenditure invested into a child each and every time period. These instruments must also be uncorrelated with ε_{ijt} which

Table 2: Endogenous Inputs and Instruments

Endogenous Input	**Measurement/Data**	**Instrument/Identification**
Educational Expenditures E_{ijt}	Annual educational expenditure on a child reported by the primary caregiver of the child.	Gender time and occupation specific weighted average wages of parents interacted with parental time IV
Parental Time T_{imt}/T_{ift}	Number of months mother/father is present in the household to accompany the child at time t.	Gender, time, occupation and destination specific number of contracts weighted by historic migration network.
Lagged Academic Outcome S_{ijt-1}	School test scores from DepEd admin data standardized by children nationwide in same grade	Lagged instruments for parental time and educational expenditure
Education of parent $\text{Edu}_{im}, \text{Edu}_{if}$	Highest completed education level reported by mother and father in phone survey	Λ_{ij}: Child fixed effect

only contains the contemporaneous idiosyncratic shocks as the child's education production function includes Λ_{ij}. Under the premise that the instruments for parental investments are good instruments and parental investments causally impact the child's educational outcome significantly, the lagged panel of parental investment instruments will trivially be a suitable set of instruments for the S_{ijt-1}.

4.2.1 Parental Time Investments:

In this migration context, the parental time investment into a child is equivalent to the decision to migrate. Thus, I define the instrument for the mother's/father's time input at time t as:

$$Z_{imt,\text{time}} := \sum_{d \in \mathcal{D}} N_{i\ell d} Q_{imdt} \qquad \text{and} \qquad Z_{ift,\text{time}} := \sum_{d \in \mathcal{D}} N_{i\ell d} Q_{ifdt}, \tag{14}$$

where Q_{imdt} and Q_{ifdt} are as previously defined in accordance with definition 4.1.1, and $N_{i\ell d}$ is established as in definition 4.1.2. When the number of relevant job openings, as measured by Q, increases for a parent it will be more likely that the parent will be able to migrate abroad for work. The relative impact of a fluctuation in the country-specific job openings is dictated by the historical migration networks a migrant has given their location ℓ in the Philippines. The stronger $N_{i\ell d}$ is, the greater the impact a given fluctuation or change in Q will have on the migrant's propensity to migrate. To illustrate this, consider a migrant situated in a municipality in the Bangsamoro Autonomous Region in Muslim Mindanao (BARMM), the autonomous region in the Philippines located in the southwest of Mindanao. As Islam is the predominant religion in this region, recruitment agencies based in BARMM have formed much stronger migration networks with migration destinations in the Middle East. This is because employers in these Middle Eastern migration destinations prefer OFWs who share similar cultural backgrounds. Consequently, a shock that leads to an increase in job openings in Kuwait will have a relatively larger impact on migrants in the municipality located

Table 3: Sources of Endogeneity

Endogeneity	Source/Example	Solution
Measurement Error	Retrospective panel data.	Instrumental variables
Time Varying Endogeneity	Sudden health shock to child, unexpected family death in household, unexpected health shock to migrant.	Instrumental variables
Time Invariant Endogeneity	Unobserved innate ability of a child, preferences for a child to learn and go to school	Child fixed effect and lagged instrumental variable

in BARMM when contrasted with a similar shock to job openings in Hong Kong. In summary, Q is the time, occupation, and gender-specific level of relevant job openings that act to pull a mother or father abroad. The relative differential exposure to such an exogenous fluctuation is then dependent on a given migrant's origin due to pre-existing migrant networks established by recruitment agencies.

The gender specificity of the instrument stems from the fact that the labor markets of many occupations OFWs participate in are highly gendered. For example, 97% of all OFWs who worked as domestic workers were female while 98% of all OFWs who worked in construction or jobs that require physical manual labour were male. This gender specificity of the instrument provides additional exogenous variation to assist in the identification of whether the mother or the father will migrate. Thus, it is plausible that $Z_{imt,\text{time}}$ and $Z_{ift,\text{time}}$ will be good predictors of the number of months spent at home by the mother and father at time t.

A stronger than sufficient condition for $Z_{imt,\text{time}}$ and $Z_{ift,\text{time}}$ to satisfy the exclusion restriction and be a suitable instrument is, for all $\tilde{t}$:

$$\text{Cov}\left(Z_{imt,\text{time}}, \varepsilon_{ij\tilde{t}}\right) = 0 \qquad \text{and} \qquad \text{Cov}\left(Z_{ift,\text{time}}, \varepsilon_{ij\tilde{t}}\right) = 0 \tag{15}$$

It is plausible that the contemporaneous decisions of employers in a foreign country, which dictate the number of job openings in a relevant occupation (Q), is uncorrelated with $\varepsilon_{ij\tilde{t}}$ for any $\tilde{t}$. This is because the child's idiosyncratic shock most likely stems from child or household-specific events at the migrant's household location ℓ, which would be uncorrelated with the happenings at migration destination d.

By construction, the historic network weight $N_{i\ell d}$ is defined prior to the start of the panel of data. It is therefore plausible that the formation of this network will be uncorrelated with $\varepsilon_{ij\tilde{t}}$ for any $\tilde{t}$ that is during the panel. A well-known concern regarding the use of such networks is the fact that stronger historic networks in a given origin ℓ may result in ℓ having better schooling infrastructure or amenities that impact a child's educational outcomes. However, in this context, it is not a concern as the inclusion of the child fixed effect Λ_{ij}

ensures the idiosyncratic shock $\varepsilon_{ij\tilde{t}}$ will only contain contemporaneous unobservables and any pre-existing time-invariant unobservables will be differenced out. Given this reasoning, I believe it is reasonable to assume that eq. (15) holds.

4.2.2 Educational Expenditures:

Define $W_{imdt,\text{fx}}$ and $W_{ifdt,\text{fx}}$ to be the average monthly wage in destination d in the currency of d at time t across all individuals of the same gender and occupation as the mother and father respectively. To illustrate this, consider a mother whose primary occupation is domestic work. Then if d is Hong Kong, $W_{imdt,\text{fx}}$ would be the average monthly wage in Hong Kong Dollars at time t for a female domestic worker in Hong Kong. This is the raw data that is directly observed in the DMW's administrative database. Combining this with a panel of monthly foreign exchange rates, I construct the following panel of variables:

$$W_{imdt} := W_{imdt,\text{fx}} \times \text{FX}_{dt} \qquad \text{and} \qquad W_{ifdt} := W_{ifdt,\text{fx}} \times \text{FX}_{dt}, \tag{16}$$

where FX_{dt} is the average foreign exchange rate at time t between location d and the Philippines. I then define the weighted average occupation and gender-specific wage associated with a mother and father at time t in ₱ to be:

$$W_{imt} := \sum_{d\in\mathcal{D}} \left[W_{imdt} \frac{Q_{imdt}}{\sum_{d'\in\mathcal{D}} Q_{imd't}} \right] \qquad \text{and} \qquad W_{ift} := \sum_{d\in\mathcal{D}} \left[W_{ifdt} \frac{Q_{imdt}}{\sum_{d'\in\mathcal{D}} Q_{imd't}} \right] \tag{17}$$

I define the instrument for educational expenditures into a child at time t to be the mother and father's weighted average occupation and gender-specific wage interacted with the instrument for the mother and father's time input. That is:

$$Z_{imt,\text{wage}} := W_{imt} Z_{imt,\text{time}} \qquad \text{and} \qquad Z_{ift,\text{wage}} := W_{ift} Z_{ift,\text{time}} \tag{18}$$

It is reasonable to assume that a parent's wages will be correlated with expenditures on their children. Furthermore, it is conceivable that a parent's wages will be correlated with the relevant occupation and gender-specific weighted average wage denoted by W_{imt} and W_{ift}. By transitivity, it is therefore reasonable to surmise that W_{imt} and W_{ift} are correlated with child expenditures. To capture the additional variation in the parent's earnings caused by their migration status, as foreign wages are substantially higher, I interact W_{imt} and W_{ift} with the parent's respective time instrument $Z_{imt,\text{time}}$ and $Z_{ift,\text{time}}$. Therefore, it is plausible to believe that the variables $Z_{imt,\text{wage}}$ and $Z_{imt,\text{wage}}$ will be good predictors of educational expenditures at time t.

A stronger than sufficient condition for $Z_{imt,\text{wage}}$ and $Z_{imt,\text{wage}}$ to satisfy the exclusion restrictions and be suitable instruments for educational expenditures is, for all $\tilde{t}$:

$$\text{Cov}\left(Z_{imt,\text{wage}}, \varepsilon_{ij\tilde{t}}\right) = 0 \qquad \text{and} \qquad \text{Cov}\left(Z_{ift,\text{wage}}, \varepsilon_{ij\tilde{t}}\right) = 0 \tag{19}$$

As the exclusion restriction for $Z_{imt,\text{time}}$ and $Z_{ift,\text{time}}$ was argued above, I only argue the exogeneity of W_{imt} and W_{ift}. Given the institutional settings that govern migration contracts, $W_{imdt,\text{fx}}$ and $W_{ifdt,\text{fx}}$ are by and large determined by laws, regulations, and bilateral agreements. Moreover, time-specific exchange rate fluctuations further assist with exogenous variation in W_{imdt} and W_{ifdt}. Therefore, it is plausible that W_{imt} and W_{ift} are uncorrelated with $\varepsilon_{ij\tilde{t}}$ for any $\tilde{t}$ during the panel.

4.2.3 Educational Attainment of Parents:

The educational attainment of the parents is pre-determined outside the model. Nevertheless, they are endogenous choices and the reader may be concerned that the educational attainment of the parent is correlated with unobserved characteristics and innate abilities of the parent, which, in turn, are correlated with the unobserved characteristics and endowments of the children. Under the identifying assumption that the unobserved characteristics and endowments of the child that are correlated with the parents are time invariant, these specific unobservables would captured by the child fixed effect Λ_{ij}. Therefore, the child's idiosyncratic error term ε_{ijt} is uncorrelated with the pre-determined educational attainment of the parents and can be treated as exogenous. With this in mind, it is appropriate to use educational attainment freely as an interaction term with the instruments for parental migration described above to instrument for the parental time inputs interacted with the educational attainment of the parent. Identifying variation in the data for the importance of parental education arises from the movement of parents with different levels of educational attainment into and out of the household across time for the same child.

4.2.4 Exogeneity of Grandparent Presence/Absence

From my sample of households, T_{igt} varies for only 3% of the households from the years 2015 - 2019. Variation is primarily due to the death of a grandparent. In other words, T_{igt} is essentially a constant throughout the panel for an overwhelming majority of households and does not vary with the endogenous parental time inputs of T_{imt} and T_{ipt}, the educational expenditures, or lagged test score of the child. Moreover, it is not predicted by any of the instrumental variables used to identify the endogenous inputs. This is empirically confirmed with the descriptive regressions in table 4 and table 5 below.

Table 4: Grandparent Presence Regressed on Endogenous Inputs

	Dependent variable:	
	Grandparent Presence	
Mother Absence	−0.0001 (0.0005)	
Father Absence	0.001 (0.001)	
Mother Absence × High Edu		−0.00003 (0.001)
Mother Absence × Low Edu		−0.0002 (0.001)
Father Absence × High Edu		0.001 (0.001)
Father Absence × Low Edu		0.002 (0.001)
Educational Expenditures	−0.001 (0.002)	−0.001 (0.002)
Lagged Test Score	0.001 (0.004)	0.001 (0.004)
Observations	9,600	9,600
Households	1100	1100

Note: Child Fixed Effects Included *p<0.1; **p<0.05; ***p<0.01

Table 5: Grandparent Presence Regressed on Instrumental Variables

	Dependent variable:	
	Grandparent Presence	
Mother Contracts	0.006 (0.005)	
Father Contracts	0.013 (0.009)	
Mother Contracts × Low Edu		0.008 (0.005)
Mother Contracts × High Edu		0.005 (0.008)
Father Contracts × Low Edu		0.017 (0.011)
Mother Contracts × High Edu		0.002 (0.016)
Lag Mother Contracts	0.001 (0.003)	0.001 (0.003)
Lag Father Contracts	−0.001 (0.004)	−0.001 (0.004)
Mother Wages	−0.001 (0.003)	−0.001 (0.003)
Father Wages	0.0004 (0.001)	0.001 (0.001)
Lag Mother Contracts	−0.002 (0.001)	−0.002 (0.001)
Lag Father Contracts	0.0003 (0.001)	0.0003 (0.001)
Observations (Child Year)	11,979	11,979
Households	1100	1100

Note: Child Fixed Effects Included *p<0.1; **p<0.05; ***p<0.01

Estimation & Results

5.1 Linear Child Education Production Function

I first estimate two specifications of the linear fixed effects child education production functions for the age groups 6–10 and 11–15, which correspond to h_1 and h_2 described in section 4.1.1. The first specification omits the educational attainment of the parents, while the second specification interacts the educational attainment of the parents with the absence of the parent. I define the educational attainment of the parent into "high" and "low" educational attainment as follows.

Definition 5.1.1. *Low educational attainment refers to those parents whose highest level of completed education attained was secondary school.*

Definition 5.1.2. *High educational attainment refers to those parents whose highest level of completed education attained was any sort of post-secondary education.*

I utilize parental absence rather than parental presence/time inputs when estimating the linear fixed effect specifications for ease of interpretation.[14] Parental absence is measured in months a parent is away from the household per year. Educational expenditures are measured in tens of thousands of ₱ spent per year

[14]The reader may see the analogous linear child education production function with time inputs instead of absence in appendix B, table 14.

on expenditures related to the education of the child. Specifically, this consisted of annual expenditures on school supplies, textbooks, extracurricular activities that were academically related or associated with the child's school, additional tutoring outside of the child's school, school/tuition fees, transport allowances, school allowances, expenditure on internet data and electronic devices specifically for the purposes of school work, homework or anything else related to the education of the child.

5.1.1 First Stage Regressions

Identification for the endogenous inputs arises from the set of instruments described in section 4.2. I present the first stage regression for the linear specification of children aged 11–15 with the educational attainment of the parents interacted with parental absence in table 6 below. All other first-stage regressions I have performed in this paper can be found in appendix B. The intuition and description of all other first-stage regressions are identical to what is described below. For ease of exposition and presentation in result tables, I relabel the instruments $Z_{imt,\text{time}}$, $Z_{ift,\text{time}}$, $Z_{imt,\text{wage}}$, and $Z_{ift,\text{wage}}$ as "Mother Contract", "Father Contract", "Mother Wage", and "Father Wage" respectively. In addition, I scale down the instruments by factors of 1e^3 and 1e^6 respectively to enhance the readability of the coefficient estimates.

In the following paragraph, I discuss the coefficients of interest and first-stage regression results starting from the top left corner and going down the main diagonal to the bottom right corner of table 6, which have been highlighted in blue. The co-efficient estimates of $Z_{imt,\text{time}}$ interacted with the educational attainment of the mother are positive and significant for the mother's absence interacted with the mother's educational attainment. As expected, as the number of relevant contracts increases for mothers, they will spend more time abroad. Moving down the diagonal, in columns three and four, an analogous pattern can be observed for the father's contracts interacted with the father's educational attainment. In column five, educational expenditures are predicted well by $Z_{imt,\text{wage}}$, and $Z_{ift,\text{wage}}$ with significantly positive coefficients. Finally, in column six the lagged test score of the child is significantly and negatively impacted by $Z_{imt-1,\text{time}}$ and $Z_{ift-1,\text{time}}$. This reflects the fact that as $Z_{imt-1,\text{time}}$ and $Z_{ift-1,\text{time}}$ increase, the mother and father's absence in the previous period will increase, therefore having a negative impact on the child's lagged test score. Conversely, as $Z_{imt-1,\text{wage}}$, and $Z_{ift-1,\text{wage}}$ increase, the potential educational expenditures on the child in the previous period can increase, therefore having a positive impact on the child's lagged test score. This is reflected by the positive significant coefficients in the bottom right-hand corner. In summary, the signs of the estimated coefficients in the first stage regression behave in a sensible way as predicted in section 4.2. Moreover, the strength of the instruments is not a concern as the relevant F-statistics are above 10 and the global Cragg-Donald Wald F-statistic is 39.35.

Table 6: First Stage Regressions: Age 11 - 15 with Parental Education Interaction

	Dependent variable:					
	Mother Abs Low Edu	Mother Abs High Edu	Father Abs Low Edu	Father Abs High Edu	Educational Expenditure	Lagged Test Score
Mother Contract × Low Edu	2.951^{***} (0.297)	0.012 (0.108)	0.055 (0.206)	0.020 (0.114)	0.164^{***} (0.055)	-0.043^{**} (0.021)
Mother Contract × High Edu	-0.335^{**} (0.149)	3.471^{***} (0.330)	-0.024 (0.208)	-0.127 (0.108)	0.130^{**} (0.066)	-0.068^{***} (0.018)
Father Contract × Low Edu	0.119 (0.260)	-0.102 (0.272)	5.618^{***} (0.436)	-0.194^{**} (0.096)	0.046 (0.062)	0.003 (0.025)
Father Contract × High Edu	0.265 (0.446)	-0.061 (0.313)	-0.159 (0.268)	4.992^{***} (0.690)	0.718^{***} (0.224)	-0.076^{**} (0.036)
Mother Wage	0.368^{***} (0.074)	0.418^{***} (0.095)	-0.021 (0.041)	-0.036^{*} (0.021)	0.320^{***} (0.031)	-0.013^{**} (0.006)
Father Wage	-0.015 (0.040)	-0.044 (0.033)	0.150^{***} (0.039)	0.181^{***} (0.041)	0.179^{***} (0.030)	0.013^{***} (0.005)
Lag Mother Contract	-0.282^{***} (0.075)	-0.171^{***} (0.060)	0.114^{*} (0.066)	0.074^{**} (0.036)	0.132^{***} (0.033)	-0.063^{***} (0.011)
Lag Father Contract	-0.116 (0.081)	0.048 (0.074)	-0.406^{***} (0.085)	-0.038 (0.050)	0.269^{***} (0.049)	-0.045^{***} (0.016)
Lag Mother Wage	0.061^{*} (0.036)	0.192^{***} (0.046)	0.005 (0.045)	-0.006 (0.016)	0.097^{***} (0.026)	0.028^{***} (0.006)
Lag Father Wage	0.083^{**} (0.038)	0.027 (0.028)	0.029 (0.025)	0.084^{**} (0.033)	0.032 (0.027)	0.044^{***} (0.007)
Observations (Child Year)	5137	5137	5137	5137	5137	5137
F-Statistic	21.38	22.95	62.87	22.85	40.31	18.82
Sanderson-Windmeijer F-Statistic	37.50	53.09	64.61	25.87	44.16	38.01

Note: Number of Households 791. Clustering of SE at household level. Child FE included. *p<0.1; **p<0.05; ***p<0.01

Global Cragg-Donald Wald F-statistic is 39.35.

5.1.2 Linear Production Function Estimates

The first and second leftmost columns of table 7 display the estimated coefficients for h_1 and h_2 respectively where the educational attainment of the parents are omitted. The third and fourth columns from the left of table 7 display the estimated coefficients for h_1 and h_2 respectively where the parent's educational attainment is interacted with their absence. The reader may immediately see that the negative impact of a mother's absence is significantly greater when the child is between the ages of 6 - 10 relative to when the child is 11 - 15. When the child is in middle childhood, a single month of maternal absence is predicted to decrease the child's academic performance relative to all other children in the same age group in the Philippines by 0.061 standard deviations. By comparison, a month of maternal absence when the child is in early adolescence will only decrease the child's academic performance relative to all other children in the same age group in the Philippines by 0.029 standard deviations. This differential impact of 0.032, standard deviations for the mother's absence across the two age groups is significantly different from zero based on linear hypothesis testing.[15]. This finding is robust to the specification where the mother's absence is interacted with her educational attainment. Moreover, the point estimates indicate that the absence of a mother with higher education will negatively impact the child's educational outcomes more greatly than a mother with low education.

Similarly, the father's absence is substantially more important when the child is between the ages of 6–10 relative to when the child is between the ages of 11–15. A month of the father's absence when the child is between the ages of 6–10 will decrease the child's academic performance by 0.029 standard deviations.
Similarly, the father's absence is substantially more important when the child is between the ages of 6–10 relative to when the child is between the ages of 11–15. A month of the father's absence when the child is between the ages of 6–10 will decrease the child's academic performance by 0.029 standard deviations. By comparison, when the child matures the impact of a month of the father's absence is not significantly different from zero. Again, this result is robust when I interact the father's absence with the father's education level. The point estimates also suggest that the time inputs of a father with a high level of education are more productive relative to a father with a low level of education. In particular, when the child is older the absence of a father with high education remains significantly impactful in decreasing the child's academic outcomes by 0.027 standard deviations, while the absence of a father with low education has no significant impact.

The findings consistently indicate the mother's absence has a greater negative impact compared to the father's absence at all age levels. When the child is between 6–10 years old, for every month of parental absence, the mother will negatively impact the child's academic outcomes by approximately 0.03 standard deviations more than the father. This 0.03 standard deviation difference is significant and robust even with the inclusion of the parent's education level when comparing mothers with high (low) education levels to fathers with high (low) education levels. When the child is between 11–15 years old, this difference falls to approximately 0.02 standard deviations and remains robust when comparing mothers with low levels of education to fathers with low levels of education. When comparing highly educated mothers and fathers, the point estimates reveal there is a 0.01 standard deviation difference. As a consequence of the mother's time being consistently more important than the father's time, it is not surprising that I also find the presence of a grandparent in the household

[15]Please refer to appendix B for all linear hypothesis tests

Table 7: Linear Child Fixed Effects Education Production Function

	Dependent variable:			
	Nationwide Age Standardized Test Score			
	Age 6 - 10	Age 11 - 15	Age 6 - 10	Age 11 - 15
Mother Absence	-0.061^{***} (0.007)	-0.029^{***} (0.007)		
Mother Absence × High Edu			-0.070^{***} (0.010)	-0.037^{***} (0.008)
Mother Absence × Low Edu			-0.057^{***} (0.008)	-0.023^{***} (0.009)
Mother Absence × Grandparent	0.022^{***} (0.008)	-0.002 (0.009)	0.021^{**} (0.008)	-0.004 (0.010)
Father Absence	-0.029^{***} (0.006)	-0.008 (0.008)		
Father Absence × High Edu			-0.042^{***} (0.011)	-0.027^{*} (0.015)
Father Absence × Low Edu			-0.024^{***} (0.006)	-0.002 (0.008)
Father Absence × Grandparent	0.026^{***} (0.008)	-0.002 (0.011)	0.028^{***} (0.009)	0.002 (0.011)
Educational Expenditures	0.068^{***} (0.025)	0.147^{***} (0.024)	0.081^{***} (0.028)	0.154^{***} (0.025)
Lag Test Score	0.218^{***} (0.049)	0.476^{***} (0.093)	0.231^{***} (0.052)	0.503^{***} (0.090)
Grandparent Presence	-0.235^{**} (0.094)	0.184 (0.151)	-0.249^{**} (0.097)	0.163 (0.157)
Observations	5,083	5,348	5,083	5,348
Number of Households	1072	876	1072	876
Cragg-Donald Wald F statistic	52.74	46.17	37.039	39.35

Note: Clustered standard errors at household level. *p<0.1; **p<0.05; ***p<0.01

never is able to fully substitute for a mother's time and negate the adverse impact a mother's absence may have on the child. By contrast, the presence of grandparents is able to fully ameliorate the negative impact of a father's absence in all cases except for when the child is older and the father has attained a higher education.

These findings also reveal that educational expenditures are significantly more important when the child is between the ages of 6–10 compared to when the child is 11–15 years of age. Under the preferred specification that includes a parent's educational attainment, for every additional 10,000 ₱ spent per year on educational expenditures, a child's academic outcomes are increased by 0.068 standard deviations when the child is 6–10 years of age. By contrast, when the child is 11–15 years of age, for every additional 10,000 ₱ spent per year on educational expenditures, the child's academic outcomes will be increased by 0.147 standard deviations. Finally, using the linear specification with the inclusion of the parent's educational attainment I further breakdown each age group into boys and girls. The same general findings and relative magnitudes appear for all point estimates. However, no significant differences between the point estimates appear between boys and girls with linear hypothesis testing. The results from this can be found in table 16 in appendix B.

5.2 Calculating Net Impacts of Migration:

Using the estimates from the linear fixed effects specification of the education production function I perform an accounting exercise to obtain a range for the net impact of migration on a child's educational outcome conditional on the age of the children, gender of the migrant, and educational attainment of the migrant. These computations are summarized for children between the ages of 6 and 10, and those aged between 11 and 15 in table 8 and table 9 respectively.

Table 8: Net Impact of Temporary Migration: Children Age 6 - 10

	Parental Absence	Potential Additional Income (PHP/month)	Net Impact Range
<u>Female</u>			
Low Skill (e.g. Domestic Worker)	-0.057	₱18,000	$[-0.052, -0.045]$
High Skill (e.g. Nurse)	-0.070	₱115,000	$[-0.042, 0.008]$
<u>Male</u>			
Low Skill (e.g. Construction)	$-$ 0.024	₱13,000	$[-0.021, -0.015]$
High Skill (e.g. Engineer)	$-$ 0.042	₱155,000	$[-0.004, 0.062]$

Table 9: Net Impact of Temporary Migration: Children Age 11 - 15

	Parental Absence	Potential Additional Income (PHP/month)	Net Impact Range
<u>Female</u>			
Low Skill (e.g. Domestic Worker)	-0.023	₱18,000	$[-0.015, 0.0001]$
High Skill (e.g. Nurse)	-0.032	₱115,000	$[0.021, 0.116]$
<u>Male</u>			
Low Skill (e.g. Construction)	$-$ 0.002	₱13,000	$[0.004, 0.015]$
High Skill (e.g. Engineer)	$-$ 0.027	₱155,000	$[0.045, 0.172]$

I first calculate W_{mt} and W_{ft} as I do in eq. (17) for the most common occupations among mothers and fathers that require low and high levels of educational attainment. These occupations are domestic workers and nurses for mothers, and low-skilled construction workers and engineers for fathers. I then calculate the average wage in the Philippines for these corresponding occupations and take the difference to obtain the average wage gain for a migrant in these four occupations rounded up to the nearest thousand ₱. This average wage gain for each occupation is reported in column two of table 8 and table 9. Using the estimated coefficients of the linear production function in columns three and four of table 7 I calculate the maximum possible increase in the child's test score under the assumption that all of the additional income gained from working abroad is spent on educational expenditures for the child.[16] Furthermore, from the collected data I also note that households, on average, allocate 36% of their total household income to educational costs. Consequently, I compute a more conservative estimate for the increase in a child's test scores by assuming that only 36% of the additional income earned from migration is directed towards increased educational expenditures for the child. Finally, I take the difference between the estimated coefficient for parental absence from columns three and four of table 7 for mothers and fathers with high and low educational attainment and the above calculated increased test scores. This gives a lower and upper bound of migration impacts on children, which are displayed in column four.

I find for children aged 6–10, mothers and fathers with low educational attainment who also work in a low skilled occupation will not be able to compensate for the negative impact of their absence even if they spend all of their additional income gained from working abroad on the child's educational outcomes. Nevertheless, it is marginally possible for a mother or father with a high educational attainment who also works in a high skilled occupation to compensate for their absence if they were to spend all additional income earned from migrating on the educational expenditures of their children. This reflects the notion that parental time is far more important relative to educational expenditures in determining a child's educational outcomes when a child is young. Conversely, when children are aged 11–15, mothers and fathers are always potentially able to compensate for their absence with the additional income earned. However, this is only marginal for those with low educational attainment who also work in low skill occupations. Nevertheless, it is important to note that these calculations are derived from the linear fixed effects specification of the education production function, which comes with several strong and unrealistic assumptions. It is for this primary reason I estimate a more complex specification of the child's education production function.

5.3 Triple Nested CES Child Education Production Function

5.3.1 Motivation for Triple Nested CES Specification

The estimates from the linear fixed effects specification of the child education production function are important for two key reasons. Firstly, it provides the reader with an easily interpretable set of results, which additionally permits the simple accounting exercise for the net impact of migration performed above. Secondly, it provides a clear understanding of standard first-stage regressions that verify the validity of the instrumental variable strength. However, the assumption of linearity implies that there is perfect substitutability between inputs. Moreover, the marginal returns to inputs are constant and not diminishing. These two assumptions are strong and unrealistic. With the end goal of estimating the preference parameters in the household's optimization problem, I require a more flexible specification of the child's education production function in order to match moments in the data and adequately reflect the behavior of the parents. I, therefore, assume that the age-specific education production function takes on the following triple-nested CES functional form:

$$S_{ijt} = \left[\gamma S_{ijt-1}^{\rho} + (1-\gamma)\left[\left(\alpha T_{it}^{\eta} + (1-\alpha)\, E_{ijt}^{\eta}\right)^{\frac{1}{\eta}}\right]^{\rho}\right]^{\frac{1}{\rho}} \exp\left[\Lambda_{ij} + \varepsilon_{ijt}\right], \tag{20}$$

[16]Note the estimated coefficient in table 7 is given in terms of 10,000's ₱ per year. I therefore take this coefficient and divide it by twelve before multiplying it by the additional income gained from working abroad.

where T_{it} is the following CES aggregations of time inputs from the mother, the father and the grandparents:

$$T_{it} = \begin{pmatrix} \beta_1 \left(\varphi_1 T_{imt} \mathbb{1}_{imt,\text{Low Edu}} + \varphi_2 T_{imt} \mathbb{1}_{ift,\text{High Edu}}\right)^{\xi} \\ +\beta_2 \left(\varphi_3 T_{ift} \mathbb{1}_{ift,\text{LowEdu}} + \varphi_4 T_{ift} \mathbb{1}_{ift,\text{High Edu}}\right)^{\xi} \\ +\beta_3 T_{igt}^{\xi} \end{pmatrix}^{\frac{1}{\xi}} \tag{21}$$

The inclusion of the lagged academic outcome S_{ijt-1} in the first nest with weight γ and substitution parameter ρ allows for the child to build upon their previous levels of human capital. The multiplicative interaction of Λ_{ij} through the exponential function further allows for the inputs into the education production function to be more productive given investments prior to the beginning of the observed panel of data. This reflects evidence from prior literature, which suggests the existence of dynamic complementarities between past inputs that enter through prior accumulated human capital and current inputs Agostinelli and Wiswall [2023], Caucutt et al. [2022], Attanasio et al. [2020b, 2017], Cunha et al. [2010].

The second nest between current inputs of parental time and educational expenditures places weight α on parental time inputs. The substitution parameter η permits the degree of substitutability or complementarity between past inputs and current inputs, as captured by ρ, is potentially different from the opportunity cost that the parent faces when they choose to either migrate and earn significantly more money versus spending time at home with their children but earning less money, as captured by η. The third CES aggregation of time inputs in the innermost nest, eq. (21), similarly reflects the idea that the degree of substitutability or complementarity between time and monetary inputs can be potentially different from the complementarity of substitutability of time between key caregivers of a child, namely the mother, father, and grandparents, as captured b ξ.

5.3.2 Triple Nested CES Production Function Estimates

The twelve-dimensional vector parameters in the triple nested CES production function

$$\theta_h := (\gamma, \alpha, \rho, \eta, \xi, \beta_1, \beta_2, \beta_3, \varphi_1, \varphi_2, \varphi_3, \varphi_4), \tag{22}$$

is estimated using Generalized Method of Moments where the moment condition is the orthogonality between the set of instruments used in the first stage regression described in table 6, which I will denote by Z_{ijt}, and the idiosyncratic error term ε_{ijt} i.e. $\mathbb{E}\left[Z_{ijt}\varepsilon_{ijt}\right] = 0$.[17] The results from the estimation of the triple nested CES production function for children aged 6–10 and 11–15 are displayed in table 10. Consistent with the linear fixed effects specification, the estimated weight on parental time (α) decreases from 0.652 when the child is 6 - 10 to 0.289 when the child is 11 - 15. That is, the importance of parental time decreases while the importance of educational expenditures increases as the child matures from the age group of 6–10 to 11–15. Moreover, the point estimates for the weights on the mother's time (β_1) and the father's time (β_2), are also consistent with the findings that the mother's time is always more productive than the father's time. The productivity of a mother or father's time who has a high level of educational attainment is always greater than a mother or father with a low education level as indicated by $\varphi_1 > \varphi_2$ and $\varphi_3 > \varphi_4$. However, the

[17] For the specific details on the GMM estimation procedure applied to estimate θ_h, please refer to appendix C

Table 10: Tripled Nested CES Education Production Function

	Dependent variable:	
	Nationwide Age Standardized Test Score	
	Age 6 - 10	Age 11 - 15
γ: Weight on Lagged Test Score (S_{ijt-1})	0.402	0.157
α: Weight on Parental Time	0.652	0.289
$\frac{1}{1-\rho}$: Elasticity of Substitution (S_{ijt-1} & Current Inputs)	1.91	47.61
$\frac{1}{1-\eta}$: Elasticity of Substitution (Time & Edu Expenditures)	0.20	0.46
$\frac{1}{1-\xi}$: Elasticity of Substitution (Mother, Father, Grandparents Time)	0.20	3.00
β_1: Weight on Mother's Time	0.449	0.527
β_2: Weight on Father's Time	0.294	0.473
β_2: Weight on Grandparent Presence	0.257	0.001
φ_1: Mother Time $\times$ High Edu	8.002	4.545
φ_2: Mother Time $\times$ Low Edu	4.467	3.984
φ_3: Father Time $\times$ High Edu	7.107	7.656
φ_4: Father Time $\times$ Low Edu	2.878	6.152
Observations (Child Year)	4762	5137
Number of Households	942	791

Note: Confidence Intervals to be calculated with 100 bootstrap replications. Clustering at the household level.

increase in productivity from a parent with higher education is greatly diminished as the child becomes older, most likely because the relative importance of time diminishes as the child becomes older.

I find that the elasticity of substitution between time inputs and educational expenditures, denoted by $\frac{1}{1-\eta}$, increases from 0.20 to 0.46 when the child matures from middle childhood (ages 6 - 10) to early adolescence (ages 11 - 15). This suggests a persistent complementarity between time inputs and educational expenditures, but this complementarity weakens as the child matures. The estimates also reveal the elasticity of substitution between time inputs from the mother, father, and grandparents, denoted by $\frac{1}{1-\xi}$, increases from 0.20 to 3.00 as the child progresses from middle childhood to early adolescence. This implies that time inputs from key caregivers when the child is young are complementary. However, as the child matures and the relative importance of time inputs diminishes, the time inputs particularly from the mother and father become good substitutes for one another.

5.3.3 Backing Out Unobserved Child Endowments

Upon estimating the child's education production function I utilize latent factor analysis to estimate the child's endowments, which are unobserved to the econometrician. The child's endowments are important to back out as they are key state variables in the decision rules derived from the model that are subsequently estimated. This is made possible with the newly assembled panel of the data. More specifically, notice that when I take the logarithm of both sides of eq. (20), I obtain:

$$\log(S_{ijt}) = \log\left(\left[\gamma S^{\rho}_{ijt-1} + (1-\gamma)\left[\left(\alpha T^{\eta}_{it} + (1-\alpha)\, E^{\eta}_{ijt}\right)^{\frac{1}{\eta}}\right]^{\rho}\right]^{\frac{1}{\rho}}\right) + \Lambda_{ij} + \varepsilon_{ijt} \tag{23}$$

Then defining:

$$\text{meas}_{ijt} := \log(S_{ijt}) - \log\left(\left[\gamma S^{\rho}_{ijt-1} + (1-\gamma)\left[\left(\alpha T^{\eta}_{it} + (1-\alpha)\, E^{\eta}_{ijt}\right)^{\frac{1}{\eta}}\right]^{\rho}\right]^{\frac{1}{\rho}}\right), \tag{24}$$

I therefore have an error ridden measure of the child's endowment Λ for each time period I observe the child's academic outcomes in the panel. I therefore estimate the following latent measure model for each child:

$$\text{meas}_{ijt} := \pi_t + \lambda_t \Lambda_{ij} + \nu_{ijt}, \tag{25}$$

to back out each child's endowments. I report the signal-to-noise ratio of each measurement to the latent factor/child's endowment (Λ) in table 11 below. The signal-to-noise ratio assesses the degree of information contained in a measurement m_{ijt} relative to the measurement errors ν_{ijt}. It is computed by:

$$\text{sig}_t := \frac{(\lambda_t)^2\, \text{Var}\,(\Lambda)}{(\lambda_t)^2\, \text{Var}\,(\Lambda) + \text{Var}\,(\nu_{ijt})}, \tag{26}$$

To then subsequently estimate the decision rules with the child's endowments as one of the right hand side variables, I apply the two-step estimator proposed by [Heckman et al., 2013].[18]

Table 11: Signal to Noise Ratio for Λ

Measurement	Signal
$\text{meas}_{ij,2015}$	0.44
$\text{meas}_{ij,2016}$	0.52
$\text{meas}_{ij,2017}$	0.49
$\text{meas}_{ij,2018}$	0.41
$\text{meas}_{ij,2019}$	0.33

Note: λ_{2019} is normalized to 1

5.4 Decision Rule for Migration and Expenditure Allocation

5.4.1 Parental Migration Decision Rule

The estimated coefficients of the migrant's dynamic migration decision rule as a function of the state variables derived from the model are presented in table 12. I find that there is a large positive and significant coefficient on the average children's endowment across both parents with both high and low educational attainment. That is, as the endowments of children that are conducive to academic performance increase on average in the household, the parents become more likely to migrate. Moreover, I find that parents migrate between

[18] For the precise details of this estimation please refer to appendix C.

Table 12: Decision Rule for Parental Migration Decision

	Dependent variable:			
	Mother Absence High Edu	Mother Absence Low Edu	Father Absence High Edu	Father Absence Low Edu
Average Child Endowment	10.103^{***} (2.024)	10.715^{***} (2.173)	7.521^{***} (1.549)	15.547^{***} (3.503)
Average Lagged Test Score	0.662^{***} (0.167)	0.379^{**} (0.169)	0.431^{***} (0.107)	0.788^{***} (0.283)
Average Age of Children	0.196^{***} (0.053)	0.167^{***} (0.061)	0.048 (0.045)	0.222^{**} (0.096)
Child Gender Composition (Male)	-3.039^{***} (0.824)	-1.388^{*} (0.805)	-2.362^{***} (0.559)	-2.837^{**} (1.308)
Savings/Assets	-0.025 (0.044)	-0.169^{***} (0.041)	-0.006 (0.029)	-0.256^{***} (0.068)
Mother Contract	2.896^{***} (0.193)	3.232^{***} (0.210)	-0.335^{***} (0.126)	-0.764^{***} (0.281)
Father Contract	-1.181^{***} (0.288)	-0.930^{***} (0.338)	3.122^{***} (0.244)	2.489^{***} (0.540)
Mother Wage	0.748^{***} (0.105)	0.555^{***} (0.110)	-0.080 (0.066)	0.600^{***} (0.170)
Father Wage	-0.018 (0.073)	0.182^{**} (0.086)	0.612^{***} (0.068)	0.367^{**} (0.153)
Constant	-64.129^{***} (14.286)	-44.851^{***} (14.642)	-42.173^{***} (9.323)	-81.305^{***} (24.442)
Observations	2,366	2,645	1,675	3,336
Household	518	582	369	731

Note: Average Lag Test Score and Savings/Assets are instrumented using lagged parental contracts and wages.

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

11 and 23 days more per month for every percentage point increase in the average lagged test score across all children in the household.[19] This suggests that parents internalize the effects of their absence on their children when choosing whether to migrate, and only migrate more when they have confidence that their children will succeed academically, but will remain behind if they know their presence is needed.

The estimated coefficients on the average age of the children in row three of table 12 are all positive and significant. This suggests parents will optimally delay migration until their children are older. This observed phenomenon is driven by the combination of the financial gains to migrating and the finding that monetary resources play a considerably more significant role in shaping child human capital from the ages of 11–15, while the importance of both maternal and paternal time inputs drop off substantially as shown in table 7. Therefore, as the child matures and opportunity cost of migration decreases because the child requires less parental time inputs but benefits more from increased educational expenditures, which can be supported with higher foreign wages when the parent migrates.

However, the postponement of migration must be balanced with the immediate needs of household consumption and more alluring foreign wages and job opportunities. This is reflected in rows six to ten of table 12, which present the estimated coefficients for the relevant job openings and corresponding weighted average foreign wages for each parent defined by eq. (14) and eq. (18) respectively. More specifically, the estimated coefficients show that when a mother experiences an upsurge in the number of relevant foreign contracts made available to her, her time spent abroad will increase while the father's time spent abroad will decrease, and vice versa. This is driven by the desire for parents to avoid further separation disutility and the adverse impacts of additional parental absence on the child's educational outcomes. I also find that an increase in the corresponding weighted average wages from the relevant contracts for both parents will significantly increase the corresponding parent's time abroad. Together these results support prior findings related to the traditional drivers of migration, where a relative increase in the monetary returns of migrating for a given parent will draw him/her abroad.

5.4.2 Expenditure Allocation Decision Rule

The estimated coefficients for the linear approximation of the expenditure allocation decision rule as a function of the state variables derived from the model are presented in table 13. These estimates are obtained from a linear fixed effects regression on the subset of households with two or more children, where fixed effects specifically refer to the inclusion of household fixed effects. I find that there is a significant and positive coefficient on the child's endowments. That is, as the endowments of a child that are conducive to the academic performance of a child increase, parents will allocate more monetary resources to this child. This is most likely explained by the existence of strong complementarities between a child's endowments and parental monetary investments, which permit educational expenditures to be more productive. By contrast, for every percentage point increase in the child's lagged test score parents appear to spend 520 ₱ less on

[19]This is calculated by multiplying the highest and lowest estimated coefficient in row two of table 12 by 30 (days per month). As the average lagged test score is an endogenously determined state variable, I instrument it with the lagged parental contracts and wages defined in eq. (14) and eq. (18).

Table 13: Decision Rule for Educational Expenditure Allocation

	Dependent variable:
	Educational Expenditures (10,000 ₱ /year)
Child Endowment (Λ)	0.829*** (0.318)
Lagged Test Score	−0.052** (0.021)
Age Group: 11 - 15	0.395*** (0.042)
Gender: Male	−0.168** (0.082)
Mother Contract × Low Edu	0.119** (0.046)
Mother Contract × High Edu	0.108* (0.061)
Father Contract × Low Edu	0.016 (0.053)
Father Contract × High Edu	0.760*** (0.232)
Mother Wage	0.313*** (0.046)
Father Wage	0.179*** (0.037)
Observations	8,357
Households	812
Note: Lagged test score is instrumented using lagged parental contracts and wages	*p<0.1; **p<0.05; ***p<0.01

the child in a year.[20] This can be rationalized by the substitutability I find between the lagged test scores and educational expenditures in the child's education production function. In other words, a child's poor academic performance from the previous period can be corrected and compensated for by increasing educational expenditures. The estimates also reveal that parents appear to spend approximately 3950 ₱ more per annum on children between the ages of 11–15 relative to children between the ages of 6–10. This reflects the findings from the estimated age-specific child education production functions, which indicate that monetary resources are more critical in shaping educational outcomes from the ages of 11–15 relative to the ages of 6–10.

Rows five to ten of table 13 present the estimated coefficients for the relevant job openings and corresponding weighted average foreign wages for each parent defined by eq. (14) and eq. (18) respectively. I find that when the number of relevant foreign job opportunities increases for a mother there is always a significant increase in the educational expenditures associated regardless of the educational attainment level of the mother. Conversely, although an increase in the relevant foreign job opportunities for a father will always positively impact educational expenditures, only the estimated coefficient on relevant foreign job opportunities for a father with high educational attainment is significant. Moreover, I find a 3130 ₱ (1790 ₱) increase in educational expenditures on the child for every 10,000 ₱ increase in the weighted average foreign wages from the relevant job contracts for the mother's (father's), which are both statistically significant. This result is

[20] Because the lagged test score of the child is an endogenously determined state variable I instrument for it using the lagged parental contracts and wages as defined in eq. (14) and eq. (18).

unsurprising because as the number of relevant foreign contracts and wages for either of the parents increases, this increases the likelihood of migration for the corresponding parent. In turn, this increases the household income and therefore permits the possibility of increasing educational expenditures for the children. In addition, there is the direct effect of an increase in the foreign wages on the migrant having a higher earning potential, thereby having the direct effect of potentially increasing educational expenditures on the child.

Structural Estimation

To complement the findings of the net impacts of migration in section 5.2 I impose further structure on the household's utility maximization problem and estimate its preference parameters. In particular, I assume that the utility function from eq. (7) takes on the specific functional form:

$$\begin{aligned} U(C_t, T_{mt}, T_{ft}; S_t) := &(\theta_c + \zeta_c)\log(C_t) + (\theta_s + \zeta_s)\log(S_t) \\ &- (\psi_m + \zeta_{\psi m})\,\mathbb{1}\{T_{mt} < 1\} - (\psi_f + \zeta_{\psi f})\,\mathbb{1}\{T_{ft} < 1\} \\ &- (\psi_{mf} + \zeta_{\psi mf})\,\mathbb{1}\{T_{mt} < 1\}\,\mathbb{1}\{T_{ft} < 1\} \end{aligned} \tag{27}$$

where the constants $\psi_m, \psi_f, \psi_{mf} > 0$ are separation disutility that the mother and father receive and the vector $(\zeta_c, \zeta_s, \zeta_{\psi m}, \zeta_{\psi f}, \zeta_{\psi mf})$ is a multivariate normal vector of unobserved preference heterogeneity. I then utilize Simulated Method of Moments (SMM) to estimate the vector of preference parameters:

$$\theta_{\text{Pref}} := (\theta_c, \theta_s, \psi_m, \psi_f, \psi_{mf}) \tag{28}$$

The target moments used for estimation are the per period: (i) first and second moment of the mother and the father's percentage of time at home, (ii) first and second moment of the educational expenditures each period, (iii) correlation between the educational expenditures and the child's endowments, and, (iv) first and second moment of the children's test scores. The un-targeted moments used to check the fit of the model are the first and second moments of consumption and savings/assets across all households each period. Results from the estimation of these preference parameters using simulated method of moments, and subsequent counterfactual simulations will be updated soon here.

Conclusion

The magnitude of international migration, which currently stands at 272 million individuals, is anticipated to only continue growing with increased global mobility. While international migration opportunities can substantially boost earning potential, they also entail the challenging trade-off of parental separation from children, an issue that affects millions of families in developing countries. This paper delves into the intricate dynamics surrounding parental migration decisions, and their consequences for children's educational outcomes. I estimate a dynamic model of migrant households with an embedded age-specific child education production function. This is made possible with the new seven-year panel survey of Filipino migrants, which was combined with newly assembled administrative data from the Philippines Department of Education and the Department of Migrant Workers.

I obtained three sets of key findings. The first set of findings focuses on identifying the interaction and relative importance of parental inputs in determining a child's outcomes. I find that monetary resources play a considerably more significant role in shaping child human capital from the ages of 11–15, whereas both maternal and paternal time inputs are more critical between the ages of 6–10. Notably, a mother's time appears to be more productive in fostering human capital development relative to a father's time. Additionally, I find that the elasticity of substitution between time inputs and educational expenditures increases from 0.20 to 0.46 when the child matures from the ages of 6–10 to the ages of 11–15. This suggests there exists a persistent complementarity between time inputs and educational expenditures that weakens as the child matures. Conversely, time inputs from key caregivers when the child is young are complementary, but, as the child matures and the relative importance of time inputs diminishes, the time inputs from the mother and father become good substitutes for one another. This is reflected by the elasticity of substitution between time inputs from the primary caregivers increasing from 0.20 to 3.00 as the child progresses from the ages of 6–10 to the ages of 11–15.

The second set of findings explores the relationship between parental migration decisions and their children's needs within a dynamic framework. I find that parents internalize the impact of their migration decisions on their children's educational outcomes and are more inclined to migrate when they have confidence in their children's success and believe their presence is less essential. Furthermore, my findings underscore the positive correlation between the age of the child and parental migration decisions to migrate away. Nevertheless, the delay in parental migration, which caters to the evolving needs of children, must be balanced with the allure of higher foreign wages and job opportunities. As the monetary returns to migration increase, parents will be clearly drawn to migrate abroad. Together these findings provide a framework that integrates well-studied drivers of migration, particularly factors that influence the monetary returns to migration, with equally important factors such as the child's needs and well-being as measured by their academic success.

The third set of findings delves into the impact of parental migration on children's welfare, particularly their educational outcomes. It highlights how different factors, such as the age of the child, parental education, and the gender of the parent, influence the net impact of migration on children's education. I find that parental migration is severely detrimental to a child between the ages of 6–10 for parents with only secondary school education and are correspondingly in low-skilled work. For example, for a mother who is a domestic worker, each month of maternal absence is predicted to decrease the child's academic performance relative to all other children in the same age group in the Philippines by at least 0.045 standard deviations. Parents with higher levels of educational attainment who therefore have the ability to enter high-skilled occupations may potentially be able to have a positive net impact on their children. Conversely, parental migration when a child is between the ages of 11–15 can have a substantial positive impact on the children's educational outcomes. For example, a mother who is a nurse could potentially increase their child's test scores by 0.021 standard deviations relative to all other children in the same age group in the Philippines for every month of maternal absence when the child is 11–15.

In summary, this research serves as a valuable addition to the ongoing discourse surrounding international migration, parental migration choices, and child welfare. It is particularly important for policymakers who intend to encourage temporary migration as a means to enhance the economic welfare of families in developing countries. It emphasizes the need for a dynamic and multifaceted approach to comprehend the intricacies involved and offers new perspectives on how parental migration decisions shape the lives of children, which in turn, influence parental migration decisions themselves.

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Appendix A:
Construction of the Outcome Variable

I first in detail the administrative data collected from the two data sources at the Department of Education (DepEd): (1) The Learner Information System (LIS), (2) The Bureau of Education Assessment (BEA).

Learner Information System:

The LIS is a centralized electronic database housed at the central office of the DepEd in Manila that holds information on every child for every academic school year (starting from 2014) that the child was enrolled in school from Grades 1 - 10. They key variable collected from the LIS that is used to construct the outcome variable is a percentage test score out of 100 that is recorded for each child at the end of each academic school year a chid is enrolled at school. Henceforth, I will define this variable to be the ***Internal School Test Raw Score***. The internal school test raw score is calculated from the arithmetic average of the final grade across all of the compulsory subjects taken by that child in that school year. The tests administered within a school for each school year is precisely the same for all students in the same grade. Moreover the compulsory subjects administered by the schools are mandated by the DepEd and are also the same across all the schools. However, the internal tests administered to students by each individual school for each compulsory subject, which are used to calculate the final percentage test score recorded in the LIS for any given student, may be different from school to school.

The internal school test raw score (together with other variables and personally identifying information) is collected for every single biological child of the migrant in the migrant's household for every school year these children were enrolled in school since 2014. In addition, for each child and each school year a child was enrolled in school, I also collect the corresponding internal school test raw score for all children in the same grade of the school in that school year. This allows me to construct the following "school standardized test score" for each year t:

$$\text{School Standardized Test Score}_t := \frac{\text{Child's Test Score}_t - \text{School Mean of Test Score}_t}{\text{School Standard Deviation of Test Score}_t}. \tag{29}$$

In this equation, the "test score" is the internal school test raw score. The school mean and standard deviation is taken across all children within the same grade as the child of interest at time t.

Bureau of Educational Assessment:

The BEA is an office in the DepEd that was responsible for annually administering the National Achievement Test (NAT), a standardized set of examinations across several compulsory subjects that was required to be taken by all students in grade 3, 6, 10, and 12. The compulsory subjects tested across grade 3, 6, 10, and 12 are English, Filipino, Science and Mathematics. In addition to these four compulsory subjects, in grade 6, 10, students are tested on HeKaSi - an abbreviation of heograpiya (geography), kasaysayan (history), sibika (civics). In grade 12, HeKaSi is replaced with Social Studies. The set of standardized examinations are designed to assess the knowledge learned by students in the compulsory subjects throughout the school year for each grade.

Up until and including school year 2017, every school (and the students in the relevant grades in the school) in the Philippines was required to participate in the National Achievement Test (NAT) every single school year. For school years 2018 and 2019, only a stratified sample of schools partook the NAT. The NAT ceased to be administered after the COVID-19 Pandemic. Electronic records of the test scores for every student are kept from 2012 onwards at the BEA. For each school in my sample, I collect the average NAT test score for each compulsory subject in each of the relevant grades the school will serve, for every school year from 2012 - 2019.

Construction of the Outcome Variable:

For each school in my sample I construct the schools average NAT score across all the compulsory subjects relevant to the given grades that took the NAT for each school year from 2012 - 2019. For example, if a school that serves only grade 1 - 5 I would construct the schools average NAT score for grade 3 for school years 2012 - 2019. For a school that serves grade 1 - 12 I would construct four average NAT scores, for grades 3, 6, 10, and 12 respectively, for school years 2012 - 2019. For those schools that were in my sample but did not take part in the NAT in school year 2018 and 2019, I extrapolate the data from 2012 - 2017 to construct the would be average NAT scores for the relevant grades in that school.

Then using the nationwide distribution of NAT scores across all schools in the Philippines, I construct a grade and school specific position for each year. For example, for the arbitrary school, School A, that only services grade 1 - 6 I would construct the following two variables for each school year t:

$$\text{School A Position}_{t,\text{G3}} := \frac{\text{School A Mean NAT Score for Grade } 3_t - \text{Nationwide Mean NAT Score for Grade } 3_t}{\text{Nationwide Standard Deviation NAT Score for Grade } 3_t},$$

and similarly for School A Position$_{t,\text{G6}}$. I assume that the yearly school positions for grades 3, 6, 10, and 12 map onto the school positions for the remaining school grades in the following manner:

1. The school position for grades 1 and 2 are the same as the school position for grade 3. i.e.

$$\text{School A Position}_{t,\text{G1}} = \text{School A Position}_{t,\text{G2}} = \text{School A Position}_{t,\text{G3}} \tag{30}$$

2. The school position for grades 4 and 5 are the same as the school position for grade 6.

3. The school position for grades 7, 8, and 9 are the same as the school position for grade 10.

4. The school position for grade 11 is the same as the school position for grade 12.

Consider an arbitrary student that is in grade $g \in \{1, ..., 12\}$, at time t, attending School A. I define the student's "nationwide standardized test score" at time t, denoted by S_t to be:

$$S_t := \text{School Standardized Test Score}_t + \text{School A Position}_{t,\text{G}g} \tag{31}$$

That is, the nationwide standardized test score is the sum of the child's standardized test score relative to his or her peers in the school at that time shifted by the school's position relative to all other schools in the nation for that grade level at time t. This provides us with a mean zero variance one outcome variable where the reference group the for standardization is the population of all children in the Philippines enrolled in school who are in the same grade as the child of interest.

The nationwide standardized test score, S_t, is the main outcome variable of interest that is used to produce the estimates of the child's education production function in the linear specification. This is the preferred outcome variable over using the internal school test raw score because it provides the reader with an intuitive understanding of how much inputs matter. It is difficult to interpret the importance of an input in terms of changes in raw test score points because there is no reference point to understand how much a change in a test score point matters. Moreover, given the nature of the raw test score being constructed from school specific test scores, the interpretation for a test score change could be further obscured by school specific differences. By contrast, S_t immediately gives the reader an understanding of how much inputs matter in terms of a standard deviation change relative to all children in the same grade across the Philippines regardless of school specific differences.

I find that in the absence of standardizing the internal school test raw score, the estimates of the child's education production function in the linear specification remain robust. More specifically, the sign, relative magnitudes, and statistical significance of the coefficients do not change, although the magnitude of the coefficient estimates change. The results of these regression can be found in appendix B, table 15. For this reason, I utilize the internal school test raw score in the estimation of the triple nested CES education production function where estimation requires me to log the outcome variable, which therefore requires the outcome variable to be strictly positive.

Appendix B:
Additional Tables of Results and Robustness Checks

Table 14: Linear Child Fixed Effects Education Production Function with Time Inputs

	Dependent variable:			
	Nationwide Age Standardized Test Score			
	Age 6 - 10	Age 11 - 15	Age 6 - 10	Age 11 - 15
Mother Time	0.063*** (0.008)	0.029*** (0.007)		
Mother Time × High Edu			0.072*** (0.011)	0.037*** (0.008)
Mother Time × Low Edu			0.059*** (0.008)	0.023** (0.009)
Mother Time × Grandparent	−0.028*** (0.010)	0.002 (0.010)	−0.027*** (0.010)	0.004 (0.010)
Father Time	0.030*** (0.007)	0.008 (0.008)		
Father Time × High Edu			0.043*** (0.012)	0.027* (0.015)
Father Time × Low Edu			0.025*** (0.007)	0.002 (0.008)
Father Time × Grandparent	−0.029*** (0.009)	0.002 (0.011)	−0.031*** (0.009)	−0.002 (0.011)
Educational Expenditures	0.070*** (0.026)	0.147*** (0.024)	0.083*** (0.029)	0.154*** (0.025)
Lag Test Score	0.221*** (0.050)	0.476*** (0.093)	0.234*** (0.052)	0.503*** (0.090)
Grandparent Presence	0.387*** (0.087)	0.138 (0.098)	0.386*** (0.092)	0.138 (0.105)
Observations (Child Year)	4762	5137	4762	5137
Number of Households	942	791	942	791
Cragg-Donald Wald F statistic	53.47	41.51	37.61	35.36

Note: Clustered standard errors at household level. *p<0.1; **p<0.05; ***p<0.01

Table 15: Linear Child Fixed Effects Education Production Function with Time Inputs and Raw Test Score

	Dependent variable:			
	Raw Test Score			
	(1)	(2)	(3)	(4)
Mother Time	0.727^{***} (0.092)	0.377^{***} (0.079)		
Mother Time × High Edu			0.900^{***} (0.128)	0.450^{***} (0.089)
Mother Time × Low Edu			0.646^{***} (0.099)	0.328^{***} (0.101)
Mother Time × Grandparent	-0.273^{**} (0.117)	0.021 (0.103)	-0.256^{**} (0.120)	0.043 (0.108)
Father Time	0.375^{***} (0.081)	0.160^{*} (0.092)		
Father Time × High Edu			0.653^{***} (0.164)	0.417^{**} (0.164)
Father Time × Low Edu			0.277^{***} (0.076)	0.085 (0.088)
Father Time × Grandparent	-0.336^{***} (0.108)	-0.027 (0.118)	-0.382^{***} (0.119)	-0.074 (0.124)
Educational Expenditures	1.088^{***} (0.328)	1.665^{***} (0.272)	1.353^{***} (0.387)	1.771^{***} (0.289)
Lag Test Score	0.401^{***} (0.054)	0.459^{***} (0.098)	0.427^{***} (0.059)	0.494^{***} (0.095)
Grandparent Presence	4.668^{***} (1.115)	1.841^{*} (1.072)	4.640^{***} (1.188)	1.852 (1.146)
Observations (Child Year)	4762	5137	4762	5137
Number of Households	942	791	942	791
Cragg-Donald Wald F statistic	53.47	41.51	37.61	35.36
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 16: Linear Child Fixed Effects Education Production Function for Boys and Girls

	Dependent variable:			
	Nationwide Age Standardized Test Score			
	Age 6 - 10		Age 11 - 15	
	Boys	Girls	Boys	Girls
Mother Absence × High Edu	-0.061^{***} (0.010)	-0.079^{***} (0.018)	-0.017^{*} (0.010)	-0.051^{***} (0.012)
Mother Absence × Low Edu	-0.056^{***} (0.010)	-0.055^{***} (0.012)	-0.005 (0.011)	-0.038^{***} (0.014)
Mother Absence × Grandparent	0.016 (0.012)	0.029^{**} (0.012)	-0.014 (0.012)	0.001 (0.013)
Father Absence × High Edu	-0.024^{*} (0.013)	-0.060^{***} (0.017)	-0.009 (0.016)	-0.047^{*} (0.027)
Father Absence × Low Edu	-0.024^{**} (0.011)	-0.025^{***} (0.008)	0.014 (0.011)	-0.015 (0.011)
Father Absence × Grandparent	0.024^{*} (0.013)	0.037^{***} (0.013)	-0.008 (0.014)	0.009 (0.017)
Educational Expenditures	0.049^{*} (0.027)	0.105^{*} (0.058)	0.095^{***} (0.028)	0.200^{***} (0.043)
Lag Test Score	0.221^{***} (0.053)	0.244^{***} (0.087)	0.584^{***} (0.129)	0.483^{***} (0.120)
Grandparent Presence	-0.214 (0.144)	-0.335^{**} (0.160)	0.135 (0.190)	0.279 (0.236)
Observations	2456	2306	2517	2620
Number of Households	599	561	525	517
Cragg-Donald Wald F statistic	23.78	14.36	14.29	21.705

Note: Clustered standard errors at household level. *p<0.1; **p<0.05; ***p<0.01

Table 17: Decision Rule for Parental Migration with Future Wages

	Dependent variable:			
	Mother Absence High Edu	Mother Absence Low Edu	Father Absence High Edu	Father Absence Low Edu
Average Child Endowment	9.976*** (1.989)	10.697*** (2.248)	7.039*** (1.457)	15.063*** (3.427)
Average Lagged Test Score	0.628*** (0.169)	0.368** (0.180)	0.345*** (0.105)	0.727** (0.285)
Average Age of Children	0.198*** (0.052)	0.166*** (0.063)	0.048 (0.043)	0.224** (0.093)
Child Gender Composition (Male)	−2.885*** (0.823)	−1.335 (0.845)	−1.955*** (0.520)	−2.564** (1.302)
Savings/Assets	−0.033 (0.045)	−0.179*** (0.042)	−0.034 (0.027)	−0.251*** (0.065)
Mother Contract	2.896*** (0.193)	3.232*** (0.210)	−0.335*** (0.126)	−0.764*** (0.281)
Father Contract	−1.181*** (0.288)	−0.930*** (0.338)	3.122*** (0.244)	2.489*** (0.540)
Mother Wage	0.634*** (0.101)	0.579*** (0.104)	0.024 (0.059)	0.618*** (0.151)
Father Wage	0.017 (0.059)	0.168** (0.082)	0.453*** (0.064)	0.238* (0.142)
Future Mother Wage	0.186*** (0.063)	−0.001 (0.065)	−0.027 (0.037)	−0.012 (0.098)
Future Father Wage	−0.022 (0.049)	0.033 (0.066)	0.265*** (0.039)	0.177* (0.102)
Constant	−61.630*** (14.354)	−44.080*** (15.529)	−35.370*** (9.106)	−76.345*** (24.546)
Observations	2,366	2,645	1,675	3,336
Household	518	582	369	731

Note: Average Lag Test Score and Savings/Assets are instrumented using lagged parental contracts and wages.

*p<0.1; **p<0.05; ***p<0.01

Table 18: First Stage Regressions: Age 6 - 10

	Dependent variable:					
	Mother Absence	Father Absence	Educational Expenditure	Lagged Test Score	Mother Absence × Grandparent	Father Absence × Grandparent
Mother Contracts	3.017*** (0.249)	0.099 (0.176)	0.128** (0.052)	−0.068*** (0.017)	−0.180* (0.093)	0.089 (0.056)
Father Contracts	0.079 (0.254)	5.312*** (0.331)	0.253** (0.107)	−0.094*** (0.029)	−0.103 (0.140)	0.403*** (0.153)
Mother Wage	1.207*** (0.134)	−0.091* (0.049)	0.320*** (0.042)	−0.011 (0.007)	0.451*** (0.071)	−0.017 (0.031)
Father Wage	−0.051 (0.044)	0.279*** (0.061)	0.151*** (0.043)	0.015*** (0.005)	0.053* (0.031)	0.120*** (0.031)
Lag Mother Contracts	−0.545*** (0.086)	0.165** (0.064)	0.097*** (0.027)	−0.157*** (0.015)	−0.153** (0.066)	0.056 (0.039)
Lag Father Contracts	−0.049 (0.100)	−0.456*** (0.069)	0.266*** (0.040)	−0.156*** (0.019)	0.050 (0.083)	−0.196*** (0.046)
Lag Mother Wage	0.291*** (0.081)	0.061 (0.042)	0.044 (0.037)	−0.003 (0.008)	0.141*** (0.047)	0.076*** (0.027)
Lag Father Wage	0.180*** (0.044)	0.054 (0.035)	0.042 (0.041)	0.031*** (0.007)	0.121*** (0.035)	−0.008 (0.022)
Mother Contracts × Grandparent	−0.067 (0.286)	−0.301 (0.208)	0.028 (0.059)	0.027 (0.021)	3.325*** (0.252)	−0.506*** (0.165)
Father Contracts × Grandparent	0.909** (0.405)	0.137 (0.415)	−0.078 (0.126)	0.072** (0.033)	1.019*** (0.384)	4.592*** (0.393)
Observations (Child Year)	4762	4762	4762	4762	4762	4762
F-Statistic	72.72	83.46	23.41	28.07	26.15	32.39
Sanderson-Windmeijer F-Statistic	46.57	71.65	20.67	55.09	35.38	64.50

Note: Number of Households 942. Clustering of SE at household level. Child FE included. *p<0.1; **p<0.05; ***p<0.01

Table 19: First Stage Regressions: Age 11 - 15

	Dependent variable:					
	Mother Absence	Father Absence	Educational Expenditure	Lagged Test Score	Mother Absence × Grandparent	Father Absence × Grandparent
Mother Contracts	3.038*** (0.265)	−0.020 (0.182)	0.144*** (0.052)	−0.053*** (0.016)	−0.003 (0.080)	0.187*** (0.071)
Father Contracts	0.067 (0.321)	5.263*** (0.405)	0.230** (0.100)	−0.019 (0.024)	−0.010 (0.090)	0.458*** (0.164)
Mother Wage	0.787*** (0.153)	−0.057 (0.045)	0.317*** (0.031)	−0.012** (0.006)	0.261*** (0.068)	−0.00003 (0.039)
Father Wage	−0.058 (0.057)	0.325*** (0.058)	0.188*** (0.033)	0.012*** (0.005)	0.040 (0.030)	0.095*** (0.032)
Lag Mother Contracts	−0.454*** (0.091)	0.192** (0.075)	0.125*** (0.033)	−0.063*** (0.011)	−0.198*** (0.062)	0.003 (0.049)
Lag Father Contracts	−0.064 (0.107)	−0.454*** (0.094)	0.278*** (0.052)	−0.046*** (0.016)	0.007 (0.069)	−0.220*** (0.062)
Lag Mother Wage	0.253*** (0.066)	−0.002 (0.046)	0.098*** (0.025)	0.028*** (0.006)	0.139*** (0.036)	0.053 (0.035)
Lag Father Wage	0.111** (0.049)	0.111*** (0.042)	0.034 (0.028)	0.044*** (0.007)	0.066** (0.031)	0.017 (0.031)
Mother Contracts × Grandparent	0.052 (0.338)	−0.169 (0.218)	0.038 (0.066)	0.001 (0.021)	3.158*** (0.264)	−0.514*** (0.169)
Father Contracts × Grandparent	0.875* (0.461)	0.324 (0.586)	−0.035 (0.133)	0.039 (0.031)	0.636* (0.326)	4.810*** (0.523)
Observations (Child Year)	5137	5137	5137	5137	5137	5137
F-Statistic	53.97	80.67	45.37	22.05	26.13	28.92
Sanderson-Windmeijer F-Statistic	50.58	54.61	45.37	37.06	44.14	32.78

Note: Number of Households 791. Clustering of SE at household level. Child FE included. *p<0.1; **p<0.05; ***p<0.01

Table 20: First Stage Regressions: Age 6 - 10 with Education Interaction

	Dependent variable:					
	Mother Abs Low Edu	Mother Abs High Edu	Father Abs Low Edu	Father Abs High Edu	Educational Expenditure	Lagged Test Score
Mother Contract × Low Edu	3.135^{***} (0.319)	-0.144 (0.106)	0.062 (0.197)	0.140 (0.091)	0.137^{**} (0.055)	-0.070^{***} (0.019)
Mother Contract × High Edu	-0.567^{***} (0.156)	3.663^{***} (0.255)	0.079 (0.200)	-0.154 (0.095)	0.153^{**} (0.067)	-0.068^{***} (0.023)
Father Contract × Low Edu	-0.081 (0.286)	-0.137 (0.173)	5.711^{***} (0.396)	-0.200^{**} (0.094)	-0.002 (0.075)	-0.055^{*} (0.031)
Father Contract × High Edu	0.744^{**} (0.327)	-0.081 (0.247)	-0.019 (0.171)	4.943^{***} (0.449)	0.758^{***} (0.206)	-0.171^{***} (0.039)
Mother Wage	0.572^{***} (0.077)	0.633^{***} (0.088)	-0.067^{*} (0.037)	-0.020 (0.029)	0.320^{***} (0.042)	-0.011^{*} (0.007)
Father Wage	-0.014 (0.032)	-0.043 (0.028)	0.100^{***} (0.023)	0.181^{***} (0.050)	0.145^{***} (0.043)	0.016^{***} (0.006)
Lag Mother Contract	-0.320^{***} (0.067)	-0.222^{***} (0.061)	0.083 (0.058)	0.078^{**} (0.031)	0.100^{***} (0.027)	-0.157^{***} (0.015)
Lag Father Contract	-0.113 (0.083)	0.050 (0.067)	-0.376^{***} (0.063)	-0.068^{**} (0.032)	0.254^{***} (0.040)	-0.154^{***} (0.019)
Lag Mother Wage	0.110^{**} (0.048)	0.180^{***} (0.054)	0.062^{*} (0.037)	0.001 (0.020)	0.042 (0.037)	-0.003 (0.008)
Lag Father Wage	0.090^{***} (0.032)	0.086^{***} (0.026)	-0.007 (0.017)	0.063^{**} (0.029)	0.038 (0.041)	0.032^{***} (0.007)
Observations (Child Year)	4762	4762	4762	4762	4762	4762
F-Statistic	29.12	28.46	45.26	34.70	20.45	24.16
Sanderson-Windmeijer F-Statistic	40.09	35.48	77.23	36.68	16.07	55.56

Note: Number of Households 942. Clustering of SE at household level. Child FE included. *p<0.1; **p<0.05; ***p<0.01

Table 21: First Stage Regressions: Age 11 - 15 with Education Interaction

	Dependent variable:					
	Mother Abs Low Edu	Mother Abs High Edu	Father Abs Low Edu	Father Abs High Edu	Educational Expenditure	Lagged Test Score
Mother Contract × Low Edu	2.951*** (0.297)	0.012 (0.108)	0.055 (0.206)	0.020 (0.114)	0.164*** (0.055)	−0.043** (0.021)
Mother Contract × High Edu	−0.335** (0.149)	3.471*** (0.330)	−0.024 (0.208)	−0.127 (0.108)	0.130** (0.066)	−0.068*** (0.018)
Father Contract × Low Edu	0.119 (0.260)	−0.102 (0.272)	5.618*** (0.436)	−0.194** (0.096)	0.046 (0.062)	0.003 (0.025)
Father Contract × High Edu	0.265 (0.446)	−0.061 (0.313)	−0.159 (0.268)	4.992*** (0.690)	0.718*** (0.224)	−0.076** (0.036)
Mother Wage	0.368*** (0.074)	0.418*** (0.095)	−0.021 (0.041)	−0.036* (0.021)	0.320*** (0.031)	−0.013** (0.006)
Father Wage	−0.015 (0.040)	−0.044 (0.033)	0.150*** (0.039)	0.181*** (0.041)	0.179*** (0.030)	0.013*** (0.005)
Lag Mother Contract	−0.282*** (0.075)	−0.171*** (0.060)	0.114* (0.066)	0.074** (0.036)	0.132*** (0.033)	−0.063*** (0.011)
Lag Father Contract	−0.116 (0.081)	0.048 (0.074)	−0.406*** (0.085)	−0.038 (0.050)	0.269*** (0.049)	−0.045*** (0.016)
Lag Mother Wage	0.061* (0.036)	0.192*** (0.046)	0.005 (0.045)	−0.006 (0.016)	0.097*** (0.026)	0.028*** (0.006)
Lag Father Wage	0.083** (0.038)	0.027 (0.028)	0.029 (0.025)	0.084** (0.033)	0.032 (0.027)	0.044*** (0.007)
Observations (Child Year)	5137	5137	5137	5137	5137	5137
F-Statistic	21.38	22.95	62.87	22.85	40.31	18.82
Sanderson-Windmeijer F-Statistic	37.50	53.09	64.61	25.87	44.16	38.01

Note: Number of Households 791. Clustering of SE at household level. Child FE included. *p<0.1; **p<0.05; ***p<0.01

Table 22: First Stage Regressions: Boys Age 6 - 10

	Dependent variable:					
	Mother Absence	Father Absence	Educational Expenditure	Lagged Test Score	Mother Absence × Grandparent	Father Absence × Grandparent
Mother Contract	3.166*** (0.259)	0.107 (0.193)	0.161** (0.064)	−0.069*** (0.020)	−0.157 (0.120)	0.116 (0.083)
Father Contract	0.289 (0.292)	5.370*** (0.383)	0.297* (0.155)	−0.099** (0.040)	0.031 (0.186)	0.554** (0.245)
Mother Wage	1.118*** (0.165)	−0.080 (0.053)	0.319*** (0.055)	−0.013 (0.008)	0.418*** (0.093)	−0.025 (0.042)
Father Wage	−0.063 (0.059)	0.242*** (0.064)	0.193*** (0.045)	0.017** (0.008)	0.034 (0.044)	0.105*** (0.037)
Lag Mother Contract	−0.549*** (0.106)	0.165** (0.073)	0.112*** (0.030)	−0.166*** (0.019)	−0.172** (0.082)	0.049 (0.051)
Lag Father Contract	−0.027 (0.122)	−0.456*** (0.084)	0.293*** (0.050)	−0.170*** (0.026)	0.066 (0.111)	−0.234*** (0.064)
Lag Mother Wage	0.340*** (0.089)	0.047 (0.044)	0.067 (0.053)	−0.006 (0.010)	0.149*** (0.057)	0.045 (0.032)
Lag Father Wage	0.236*** (0.054)	0.036 (0.038)	0.035 (0.056)	0.040*** (0.009)	0.145*** (0.043)	−0.010 (0.028)
Mother Contract × Grandparent	−0.379 (0.327)	−0.164 (0.229)	0.017 (0.066)	0.048* (0.026)	3.056*** (0.318)	−0.354* (0.196)
Father Contract × Grandparent	0.724 (0.479)	0.227 (0.498)	−0.142 (0.171)	0.050 (0.048)	1.020** (0.477)	4.500*** (0.574)
Observations	2456	2456	2456	2456	2456	2456
F-Statistic	49.39	60.24	21.04	22.34	16.13	26.24
Sanderson-Windmeijer F-Statistic	34.54	43.11	18.78	39.17	20.05	33.11

Note: Number of Households 599. Clustering of SE at household level. Child FE included. *p<0.1; **p<0.05; ***p<0.01

Table 23: First Stage Regressions: Boys Age 6 - 10 with Education Interaction

	Dependent variable:					
	Mother Abs Low Edu	Mother Abs High Edu	Father Abs Low Edu	Father Abs High Edu	Educational Expenditure	Lagged Test Score
Mother Contract × Low Edu	3.102*** (0.330)	−0.031 (0.138)	0.063 (0.206)	0.121 (0.140)	0.161** (0.074)	−0.073*** (0.027)
Mother Contract × High Edu	−0.525*** (0.161)	3.833*** (0.285)	0.138 (0.214)	−0.121 (0.093)	0.189** (0.078)	−0.067*** (0.023)
Father Contract × Low Edu	−0.139 (0.323)	0.029 (0.181)	5.634*** (0.474)	−0.228** (0.101)	0.0004 (0.095)	−0.064 (0.042)
Father Contract × High Edu	1.087*** (0.398)	0.112 (0.297)	−0.049 (0.195)	5.342*** (0.525)	0.980*** (0.333)	−0.176*** (0.062)
Mother Wage	0.487*** (0.085)	0.622*** (0.113)	−0.070 (0.043)	−0.006 (0.029)	0.316*** (0.055)	−0.014 (0.008)
Father Wage	−0.018 (0.043)	−0.056 (0.040)	0.104*** (0.028)	0.138*** (0.051)	0.184*** (0.045)	0.018** (0.008)
Lag Mother Contract	−0.299*** (0.077)	−0.243*** (0.078)	0.086 (0.066)	0.078** (0.034)	0.117*** (0.029)	−0.166*** (0.019)
Lag Father Contract	−0.022 (0.105)	−0.023 (0.082)	−0.377*** (0.082)	−0.077** (0.032)	0.281*** (0.050)	−0.167*** (0.026)
Lag Mother Wage	0.096* (0.051)	0.244*** (0.067)	0.050 (0.039)	−0.002 (0.022)	0.067 (0.053)	−0.006 (0.010)
Lag Father Wage	0.126*** (0.042)	0.105*** (0.034)	−0.014 (0.018)	0.050 (0.030)	0.031 (0.055)	0.040*** (0.009)
Observations	2456	2456	2456	2456	2456	2456
F-Statistic	15.45	24.73	37.11	16.89	17.81	18.92
Sanderson-Windmeijer F-Statistic	18.11	37.22	42.56	23.76	16.58	37.36

Note: Number of Households 599. Clustering of SE at household level. Child FE included. *p<0.1; **p<0.05; ***p<0.01

Table 24: First Stage Regressions: Girls Age 6 - 10

	Dependent variable:					
	Mother Absence	Father Absence	Educational Expenditure	Lagged Test Score	Mother Absence × Grandparent	Father Absence × Grandparent
Mother Contract	2.863*** (0.342)	0.098 (0.227)	0.090 (0.066)	−0.065** (0.026)	−0.210** (0.100)	0.065 (0.055)
Father Contract	−0.155 (0.324)	5.253*** (0.412)	0.212** (0.107)	−0.082** (0.041)	−0.250* (0.147)	0.236* (0.129)
Mother Wage	1.348*** (0.189)	−0.109* (0.066)	0.319*** (0.052)	−0.007 (0.010)	0.506*** (0.091)	−0.009 (0.037)
Father Wage	−0.041 (0.047)	0.320*** (0.067)	0.104* (0.054)	0.014* (0.008)	0.072** (0.029)	0.135*** (0.033)
Lag Mother Contract	−0.549*** (0.111)	0.165** (0.083)	0.085** (0.038)	−0.147*** (0.022)	−0.137* (0.081)	0.061 (0.047)
Lag Father Contract	−0.079 (0.127)	−0.445*** (0.086)	0.231*** (0.045)	−0.142*** (0.026)	0.030 (0.097)	−0.144*** (0.050)
Lag Mother Wage	0.213* (0.115)	0.079 (0.065)	0.019 (0.034)	−0.002 (0.010)	0.124** (0.063)	0.120*** (0.036)
Lag Father Wage	0.115** (0.053)	0.075* (0.042)	0.050 (0.035)	0.023** (0.011)	0.094** (0.042)	−0.005 (0.023)
Mother Contract × Grandparent	0.276 (0.383)	−0.468* (0.273)	0.038 (0.081)	0.003 (0.031)	3.653*** (0.290)	−0.699*** (0.216)
Father Contract × Grandparent	1.171** (0.480)	0.043 (0.481)	−0.030 (0.159)	0.084* (0.046)	1.020** (0.433)	4.705*** (0.393)
Observations	2306	2306	2306	2306	2306	2306
F-Statistic	41.12	52.01	10.38	10.93	16.94	18.92
Sanderson-Windmeijer F-Statistic	27.59	49.81	12.50	20.93	33.20	37.22

Note: Number of Households 561. Clustering of SE at household level. Child FE included. *p<0.1; **p<0.05; ***p<0.01

Table 25: First Stage Regressions: Girls Age 6 - 10 with Education Interaction

	Dependent variable:					
	Mother Abs Low Edu	Mother Abs High Edu	Father Abs Low Edu	Father Abs High Edu	Educational Expenditure	Lagged Test Score
Mother Contract × Low Edu	3.147*** (0.443)	−0.255* (0.138)	0.061 (0.279)	0.158* (0.087)	0.112 (0.069)	−0.068*** (0.025)
Mother Contract × High Edu	−0.602*** (0.213)	3.451*** (0.363)	0.014 (0.255)	−0.202 (0.137)	0.091 (0.088)	−0.063 (0.043)
Father Contract × Low Edu	−0.103 (0.411)	−0.266 (0.228)	5.793*** (0.517)	−0.175 (0.115)	−0.010 (0.087)	−0.033 (0.045)
Father Contract × High Edu	0.526 (0.390)	−0.318 (0.304)	0.005 (0.215)	4.622*** (0.499)	0.590*** (0.187)	−0.170*** (0.047)
Mother Wage	0.691*** (0.120)	0.659*** (0.107)	−0.068 (0.054)	−0.043 (0.034)	0.321*** (0.052)	−0.008 (0.010)
Father Wage	−0.018 (0.035)	−0.028 (0.027)	0.096*** (0.030)	0.227*** (0.055)	0.100* (0.054)	0.014* (0.008)
Lag Mother Contract	−0.339*** (0.094)	−0.209*** (0.075)	0.082 (0.076)	0.075* (0.040)	0.086** (0.037)	−0.147*** (0.021)
Lag Father Contract	−0.198* (0.102)	0.112 (0.083)	−0.371*** (0.073)	−0.055 (0.049)	0.223*** (0.045)	−0.141*** (0.026)
Lag Mother Wage	0.113 (0.075)	0.096 (0.066)	0.076 (0.059)	0.010 (0.027)	0.015 (0.033)	−0.001 (0.010)
Lag Father Wage	0.051 (0.038)	0.061* (0.032)	0.002 (0.023)	0.078** (0.034)	0.047 (0.035)	0.023** (0.011)
Observations	2306	2306	2306	2306	2306	2306
F-Statistic	21.19	11.51	26.33	24.70	9.90	9.33
Sanderson-Windmeijer F-Statistic	31.40	14.23	40.71	22.74	9.77	21.82

Note: Number of Households 561. Clustering of SE at household level. Child FE included. *p<0.1; **p<0.05; ***p<0.01

Table 26: First Stage Regressions: Boys Age 11 - 15

	Dependent variable:					
	Mother Absence	Father Absence	Educational Expenditure	Lagged Test Score	Mother Absence × Grandparent	Father Absence × Grandparent
Mother Contract	3.416*** (0.310)	−0.062 (0.259)	0.157** (0.067)	−0.050** (0.023)	0.127 (0.130)	0.213* (0.118)
Father Contract	−0.057 (0.349)	5.533*** (0.535)	0.131* (0.073)	0.005 (0.029)	0.204* (0.110)	0.643*** (0.240)
Mother Wage	0.727*** (0.127)	−0.076 (0.055)	0.287*** (0.039)	−0.011 (0.008)	0.238*** (0.055)	0.004 (0.040)
Father Wage	−0.063 (0.070)	0.361*** (0.086)	0.157*** (0.054)	0.018** (0.008)	0.042 (0.047)	0.064 (0.050)
Lag Mother Contract	−0.510*** (0.112)	0.165 (0.104)	0.192*** (0.041)	−0.068*** (0.015)	−0.257*** (0.083)	0.029 (0.077)
Lag Father Contract	−0.224 (0.138)	−0.436*** (0.150)	0.252*** (0.065)	−0.013 (0.023)	−0.031 (0.089)	−0.253** (0.108)
Lag Mother Wage	0.226*** (0.073)	−0.019 (0.057)	0.088** (0.037)	0.028*** (0.009)	0.107*** (0.039)	0.049 (0.042)
Lag Father Wage	0.074 (0.062)	0.118* (0.066)	0.050 (0.053)	0.045*** (0.011)	0.037 (0.040)	0.025 (0.053)
Mother Contract × Grandparent	−0.335 (0.387)	−0.060 (0.283)	−0.013 (0.083)	0.006 (0.030)	2.965*** (0.308)	−0.471** (0.193)
Father Contract × Grandparent	0.842 (0.512)	0.001 (0.837)	0.011 (0.133)	0.033 (0.040)	0.352 (0.376)	4.607*** (0.726)
Observations	2517	2517	2517	2517	2517	2517
F-Statistic	39.09	75.61	21.02	10.82	19.00	24.12
Sanderson-Windmeijer F-Statistic	28.40	36.57	33.95	16.39	27.14	18.68

Note: Number of Households 525. Clustering of SE at household level. Child FE included. *p<0.1; **p<0.05; ***p<0.01

Table 27: First Stage Regressions: Boys Age 11 - 15 with Education Interaction

	Dependent variable:					
	Mother Abs Low Edu	Mother Abs High Edu	Father Abs Low Edu	Father Abs High Edu	Educational Expenditure	Lagged Test Score
Mother Contract × Low Edu	3.322*** (0.342)	0.062 (0.141)	0.141 (0.296)	−0.011 (0.100)	0.166*** (0.059)	−0.034 (0.028)
Mother Contract × High Edu	−0.247 (0.168)	3.708*** (0.389)	−0.244 (0.296)	−0.027 (0.108)	0.161* (0.095)	−0.070** (0.029)
Father Contract × Low Edu	0.087 (0.311)	−0.175 (0.285)	5.431*** (0.564)	−0.093 (0.072)	0.041 (0.063)	−0.0003 (0.032)
Father Contract × High Edu	−0.223 (0.441)	0.312 (0.498)	−0.232 (0.433)	6.894*** (0.633)	0.603*** (0.212)	0.045 (0.064)
Mother Wage	0.283*** (0.063)	0.445*** (0.086)	−0.013 (0.048)	−0.050* (0.028)	0.291*** (0.040)	−0.011 (0.008)
Father Wage	0.019 (0.047)	−0.084* (0.050)	0.162*** (0.057)	0.182*** (0.063)	0.151*** (0.055)	0.017** (0.008)
Lag Mother Contract	−0.326*** (0.093)	−0.184** (0.075)	0.059 (0.092)	0.116*** (0.044)	0.195*** (0.040)	−0.067*** (0.015)
Lag Father Contract	−0.226** (0.109)	0.004 (0.099)	−0.536*** (0.131)	0.112** (0.056)	0.257*** (0.065)	−0.013 (0.023)
Lag Mother Wage	0.040 (0.037)	0.186*** (0.052)	0.011 (0.053)	−0.029 (0.020)	0.088** (0.037)	0.028*** (0.009)
Lag Father Wage	0.075* (0.041)	−0.001 (0.044)	−0.005 (0.038)	0.119** (0.054)	0.049 (0.053)	0.045*** (0.011)
Observations	2517	2517	2517	2517	2517	2517
F-Statistic	16.45	17.22	53.87	22.76	19.79	9.20
Sanderson-Windmeijer F-Statistic	24.21	28.91	43.12	35.75	32.24	17.09

Note: Number of Households 525. Clustering of SE at household level. Child FE included. *p<0.1; **p<0.05; ***p<0.01

Table 28: First Stage Regressions: Girls Age 11 - 15

	Dependent variable:					
	Mother Absence	Father Absence	Educational Expenditure	Lagged Test Score	Mother Absence × Grandparent	Father Absence × Grandparent
Mother Contract	2.726*** (0.317)	0.021 (0.215)	0.128* (0.070)	−0.056*** (0.021)	−0.110 (0.087)	0.165*** (0.064)
Father Contract	0.130 (0.412)	5.040*** (0.497)	0.285* (0.150)	−0.030 (0.035)	−0.205* (0.119)	0.289* (0.152)
Mother Wage	0.844*** (0.212)	−0.044 (0.056)	0.353*** (0.066)	−0.015* (0.008)	0.280*** (0.096)	0.002 (0.052)
Father Wage	−0.053 (0.071)	0.308*** (0.061)	0.202*** (0.038)	0.010* (0.006)	0.044 (0.032)	0.116*** (0.032)
Lag Mother Contract	−0.398*** (0.108)	0.213** (0.083)	0.066 (0.042)	−0.059*** (0.013)	−0.151** (0.067)	−0.019 (0.048)
Lag Father Contract	0.060 (0.125)	−0.444*** (0.096)	0.286*** (0.066)	−0.072*** (0.019)	0.053 (0.077)	−0.184*** (0.057)
Lag Mother Wage	0.288*** (0.089)	0.019 (0.049)	0.104** (0.042)	0.028*** (0.008)	0.183*** (0.051)	0.055 (0.036)
Lag Father Wage	0.132** (0.065)	0.108*** (0.041)	0.024 (0.029)	0.044*** (0.008)	0.085** (0.039)	0.014 (0.030)
Mother Contract × Grandparent	0.389 (0.414)	−0.271 (0.275)	0.091 (0.081)	−0.006 (0.026)	3.330*** (0.340)	−0.566** (0.219)
Father Contract × Grandparent	0.974* (0.548)	0.610 (0.624)	−0.025 (0.185)	0.033 (0.044)	0.927** (0.396)	5.017*** (0.518)
Observations	2620	2620	2620	2620	2620	2620
F-Statistic	35.14	41.57	22.62	13.57	19.05	18.77
Sanderson-Windmeijer F-Statistic	33.35	40.46	36.10	25.14	31.31	30.28

Note: Number of Households 517. Clustering of SE at household level. Child FE included. *p<0.1; **p<0.05; ***p<0.01

Table 29: First Stage Regressions: Girls Age 11 - 15 with Education Interaction

	Dependent variable:					
	Mother Abs Low Edu	Mother Abs High Edu	Father Abs Low Edu	Father Abs High Edu	Educational Expenditure	Lagged Test Score
Mother Contract × Low Edu	2.641*** (0.379)	−0.040 (0.124)	−0.021 (0.249)	0.045 (0.159)	0.156* (0.083)	−0.051* (0.027)
Mother Contract × High Edu	−0.403** (0.183)	3.287*** (0.377)	0.167 (0.220)	−0.167 (0.108)	0.099 (0.079)	−0.063*** (0.021)
Father Contract × Low Edu	0.185 (0.311)	−0.029 (0.363)	5.849*** (0.468)	−0.229* (0.134)	0.029 (0.097)	0.017 (0.040)
Father Contract × High Edu	0.386 (0.530)	−0.261 (0.300)	−0.211 (0.257)	4.225*** (0.798)	0.728*** (0.274)	−0.114*** (0.033)
Mother Wage	0.444*** (0.112)	0.397*** (0.122)	−0.028 (0.051)	−0.020 (0.024)	0.356*** (0.066)	−0.016* (0.008)
Father Wage	−0.030 (0.050)	−0.020 (0.034)	0.145*** (0.041)	0.182*** (0.039)	0.193*** (0.033)	0.012** (0.005)
Lag Mother Contract	−0.234*** (0.088)	−0.165** (0.071)	0.164** (0.073)	0.031 (0.042)	0.074* (0.042)	−0.060*** (0.013)
Lag Father Contract	−0.025 (0.099)	0.084 (0.083)	−0.298*** (0.078)	−0.105** (0.054)	0.269*** (0.062)	−0.069*** (0.019)
Lag Mother Wage	0.082 (0.054)	0.206*** (0.061)	0.011 (0.045)	0.017 (0.022)	0.100** (0.043)	0.029*** (0.008)
Lag Father Wage	0.084* (0.049)	0.047 (0.033)	0.049** (0.025)	0.065** (0.028)	0.022 (0.028)	0.044*** (0.008)
Observations	2620	2620	2620	2620	2620	2620
F-Statistic	12.55	15.13	36.53	20.16	19.66	11.85
Sanderson-Windmeijer F-Statistic	21.57	39.78	47.45	15.61	29.90	26.02

Note: Number of Households 517. Clustering of SE at household level. Child FE included. *p<0.1; **p<0.05; ***p<0.01

Appendix C: GMM Estimation for Triple Nested CES & Latent Measure Model

10.1 GMM Estimation:

The 12-dimensional vector of parameters that are to be estimated in specification eq. (20) is:

$$\theta_h := (\gamma, \alpha, \rho, \eta, \xi, \beta_1, \beta_2, \beta_3, \varphi_1, \varphi_2, \varphi_3, \varphi_4).$$

To this end, I first take a log transformation of both sides of eq. (20) so that the error term ε_{ijt} and the child's fixed effect Λ_{ij} is additively separable, This yields eq. (23). Define the function:

$$f(S_{ijt-1}, T_{it}, E_{ijt}, \theta_h) := \left[\gamma S_{ijt-1}^{\rho} + (1-\gamma)\left[\left(\alpha T_{it}^{\eta} + (1-\alpha) E_{ijt}^{\eta}\right)^{\frac{1}{\eta}}\right]^{\rho}\right]^{\frac{1}{\rho}}, \tag{32}$$

where T_{it} is defined as in eq. (21) and the vector of parameters θ_h is defined as above. Denote $\mathbb{T}_{ij}$ to be the number of panel observations for child j in household i and define the following demeaned variable over time:

$$\widetilde{\log} S_{ijt} := \log(S_{ijt}) - \frac{1}{\mathbb{T}_{ij}} \sum_{t'=1}^{\mathbb{T}_{ij}} \log(S_{ijt'}).$$

I similarly define $\widetilde{\log}(f(S_{ijt-1}, T_{it}, E_{ijt}, \theta_h))$, $\widetilde{\Lambda}_{ij}$ and $\widetilde{\varepsilon}_{ijt}$. Noting that $\widetilde{\Lambda}_{ij} = 0$, by bemeaning both sides of eq. (23) over the panel observations for child j in household i, I therefore obtain:

$$\widetilde{\log} S_{ijt} = \widetilde{\log}(f(S_{ijt-1}, T_{it}, E_{ijt}, \theta_h)) + \tilde{\varepsilon}_{ijt} \tag{33}$$

Define:

$$\widetilde{\varepsilon}_{ijt}(\theta_h) := \widetilde{\log} S_{ijt} - \widetilde{\log}(f(S_{ijt-1}, T_{it}, E_{ijt}, \theta_h)). \tag{34}$$

Let J_i to be the number of children in household i and Z_{ijt} to be the set of instruments used in the first stage regressions for the linear education production function, as described described in table 6.[21] Then under the identifying assumption that $\mathbb{E}[\tilde{\varepsilon}_{ijt} Z_{ijt}] = 0$, where Z_{ijt} the estimator for θ_h will be the standard GMM estimator:

$$\hat{\theta}_{hn} := \underset{\theta_h \in \Theta}{\arg\min} \left[\frac{1}{n}\sum_{i=1}^{n} \frac{1}{J_i} \sum_{j=1}^{J_i} \frac{1}{\mathbb{T}_{ij}} \sum_{t=1}^{\mathbb{T}_{ij}} \widetilde{\varepsilon}_{ijt}(\theta_h) Z_{ijt}\right]' \mathbf{W} \left[\frac{1}{n}\sum_{i=1}^{n} \frac{1}{J_i} \sum_{j=1}^{J_i} \frac{1}{\mathbb{T}_{ij}} \sum_{t=1}^{\mathbb{T}_{ij}} \widetilde{\varepsilon}_{ijt}(\theta_h) Z_{ijt}\right], \tag{35}$$

where $\mathbf{W}$ is the optimal weighting matrix.

10.2 Latent Measure Model: Two Step Estimation Procedure

As the child's endowment Λ_{ij} is estimated using a latent measure model, I must account for the estimation error that is incurred when incorporating Λ_{ij} as a regressor in subsequent estimation procedures. Therefore, when estimating the parental migration decisions and educational expenditure decisions on the child, which are a function of Λ_{ij}, I follow the recommended estimation procedure in [Heckman et al., 2013]. To describe this explicitly, let me define $\hat{\Lambda}$ to be the estimated child endowment effects, and Λ to be the unobserved and

[21] Z_{ijt} is a twelve-dimensional vector of instruments,

true child endowment. Writing the regression equation for the educational expenditure decision rule I wish to estimate in the following general linear form:

$$E_{ijt} = \alpha\Lambda_{ij} + \gamma X_{ijt} + \varepsilon_{ijt} \tag{36}$$

I follow the same notation in Heckman et al. [2013] and define the matrix $\mathbf{A}$ by:

$$\mathbf{A} := \begin{bmatrix} \mathrm{Cov}\left(\hat{\Lambda}, \hat{\Lambda}\right) & \mathrm{Cov}\left(\hat{\Lambda}, X\right) \\ \mathrm{Cov}\left(X, \hat{\Lambda}\right) & \mathrm{Cov}\left(X, X\right) \end{bmatrix}^{-1} \begin{bmatrix} \mathrm{Cov}\left(\Lambda, \Lambda\right) & \mathrm{Cov}\left(\Lambda, X\right) \\ \mathrm{Cov}\left(X, \Lambda\right) & \mathrm{Cov}\left(X, X\right) \end{bmatrix}. \tag{37}$$

Then the true (and corrected) co-efficient estimates of α and γ reported in this paper are obtained by taking the naively estimated coefficients of α and γ if we do not account for this correction of Λ, and multiplying it by the inverse of the matrix $\mathbf{A}$. Standard errors, are then obtained by bootstrapping the entire procedure 100 times. This same procedure is also performed to obtain the coefficient estimates of the parental migration decision.

Appendix D: General Model and Preference Estimation

Coming soon.

Appendix E: Examples of Promotional Material

For examples of the

POEA

Bridging Recruitment to Reintegration in Migration Governance

OWWA

"I miss my mama a lot. I think about her all the time. But I know she's doing this for me to give me a brighter future."

Kabayan! Do you have a family member or a friend who is working or have previously worked abroad? We'd like to hear from them! Please help us share this post and link to a 5-minute survey.

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Migration Multi-Partner Trust Fund

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