# When Should Parents Migrate?
# The Relative Importance of Time and Money on Education from Middle Childhood to Early Adolescence.

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*It is well established that a child's educational outcomes are strongly correlated to their later socioeconomic success. This paper studies the impact of temporary migration by parents on the educational outcomes of their children who are left behind. Leveraging a novel panel dataset from the Philippines, I use gender-specific instruments for the endogenous migration decision and to estimate the child's education production function. Insert sentence about main headline result here. These results provide guidance for policy makers in developing countries who seek to utilize temporary migration as a means to alleviate poverty. This paper also contributes to the education production function estimation literature by precisely estimating age-specific impacts of maternal and paternal extensive margin time inputs.*

# Introduction

In developing countries, millions of people temporarily migrate every year in search of better employment opportunities. Many of these migrants are parents. In China alone there are 69 million children left behind by one or both parents as these parents temporarily migrate from rural to urban areas in search of work [Chen, 2013, Zhang et al., 2014]. At any one time there are approximately 2 million deployed Overseas Filipino Workers (OFWs) - Filipino citizens who temporarily migrate to another country for the sole purpose of employment. Figures estimate as many as 9 million Filipino children, which is almost one in every four children in the Philippines, who do not have a parent physically present in their life due to migration [Conde, 2008, Lam and Yeoh, 2019].

An inevitable consequence of migration by parents is parental separation. There is a fundamental tradeoff between parental time and monetary investments, which both determine a child's development and in particular educational outcomes. Understanding the relative importance of time and monetary investments on the educational outcomes of children, how a child's needs for these parental investments may change from middle childhood to early adolescence, and how this may subsequently impact the dynamic migration decision of parents is therefore critical. To answer this question, I have collected a novel retrospective seven year panel of data on 1103 migrant families from the Philippines that provides detailed information on the decisions of migrant parents and their child's academic outcomes over this time. A dynamic structural model of the migrant household is estimated using indirect inference to provide insight into how the dynamic migration decision of a parent is impacted by the needs of their children. The model also provides motivation for the first stage regression equations of the endogenous parental investments in the estimation of the linear child education production function. A non-linear child education production function is also directly estimated using generalized method of moments with the same instrumental variables.

Identifying variation in the sample of solely migrant families arises from the systematic and widespread international migration of OFW's, which results in substantial variation in parental time inputs due to parental migration and monetary investments due to remittances from higher foreign wages and exchange rate fluctuations. To exploit the power of the seven year panel I include a child fixed effect so that identification of the parameters of interest comes from comparing the same child over time. Identification of the endogenous regressors in the child education production function come from the use of a panel of instruments that are unique to the Filipino migration context. Specifically, I use a panel of gender, time, occupation, and destination specific foreign labour demand and average wages interacted with historic migrant origin-destination specific networks at the municipality level to instrument for the parental time investment and monetary investments. The lag of these instruments are used to instrument for the endogenous lagged dependent variable.

This paper makes contributions to three bodies of literature; the drivers and welfare effects of voluntary temporary migration, the impacts of voluntary temporary migration on the educational outcomes of children left behind, and the estimation of child education and cognitive skill production functions.
Focus on the costs and benefits of migration and subsequent welfare effects on families left behind in a static setting.

Somethign that is really important is that even many of these papers have talked about and looked at how migration impacts the welfare of children and education of children left behind in the past. However this is usually done in a static setting where the welfare is looked at in a single time window.
However the effect on children is highly dependent on the timing of when all of this happens! Dynamics of migration are very important. Timing is what really matters!

The overall welfare effects on children of migration are highly dependent on timing.
Dynamic structural model of household migration decisions that take into account the impact of migration on a child's educational outcomes in the next period.

In this paper, I will estimate the causal impact of the key underlying mechanisms by which temporary migration impacts the educational outcomes of LBC. To do so, I will structurally estimate the child's education production function (EPF) using an unprecedented data set from the Philippines for 6 to 12-year-old children. The educational outcomes of interest will be the child's academic ranking in their class and test scores for English, Mathematics and Filipino – the three compulsory subjects that must be taken by every child in the Philippines. The endogeneity of the migration decision by the parent is addressed by utilizing a novel gender-specific instrument that is specific to the Filipino migration context. Therefore, this paper makes significant contributions to two important literatures – namely, the literature on the impacts of temporary migration on LBC and the literature on human capital accumulation and estimation of a child's EPF.

So far, existing temporary migration literature has reached a general consensus that remittances and changes in family structure are the two primary mechanisms by which temporary migration affects educational outcomes of LBC. The remittance mechanism refers to the effect of income sent home by the migrant while changes in the family structure refer to the inevitable loss of parental time input when one parent migrates away. Reduced form approaches have been predominantly used to estimate the impact of temporary migration. This has limited the ability of researchers to disentangle and quantify the impacts of each mechanism on the educational outcome of interest. In general, the overall reduced form impact of migration on educational outcomes is presented and, depending on the dominating effect, positive impacts of temporary migration on educational outcomes have been attributed to remittances while negative impacts have been attributed to the loss of parental time input. Moreover, previous studies have not explicitly taken into account (i) the gender of the migrant, (ii) the potential impact that migration may have on family break ups and their subsequent impact on educational outcomes of LBC[1], (iii) the quality of the time inputs by the left-behind spouse or primary care takers (other than the biological parents of the child) as determined by their education level. Taking these factors into account are critical to providing a nuanced understanding of how temporary migration impacts children left behind.

[1]Within the context of the Philippines, separation of biological parents of a child and family break up is statistically far more common among migrant households. Concerns of reverse causality between family breakup and migration are addressed in more detail in the identification section.

By structurally estimating an age-specific EPF, I am able to quantify how temporary migration impacts each input that goes into the educational outcomes of a child. The various ways in which migration will impact educational outcomes can be disentangled and specifically quantified with this approach. This will be the first paper that quantifies the impact of parent-specific time inputs while accounting for heterogeneity with respect to the education level of the parent. Substitutability between parental time and the importance of primary care giver time input is able to be explored using this framework. This structural approach also allows me to distinguish the absence of a parent's time input due to migration versus parental separation by allowing these to enter into the production function as distinct variables. The identification of these inputs, which are endogenous choices made by the parents, come from novel instruments that are specific to the Filipino migration context. These instruments are discussed in detail in the identification section. Furthermore, the unique retrospective six-year panel dataset allows me to estimate the child's unobservable latent ability. Under this framework, I am able to provide policy guidance that may help migrant families choose more optimal timings for migration in order to maximize the gains LBC obtain from increased household income while minimizing the detrimental effects of parental absence and changes in family structure.

This paper also makes contributions to the child education and cognitive achievement production function (CAPF) literature. The estimation of a child's CAPF and EPF so far has faced two great challenges. Firstly, scholars have faced difficulty in observing and measuring parental time investments that go into the production function [Attanasio et al., 2020, Todd and Wolpin, 2003]. I overcome this challenge by estimating the EPF in the context of temporary migration and LBC. One could regard the migration decision as the most extreme form of a parent's time input decision. Compared to more common choice of a parent increasing their labor supply by few hours at the cost of reducing the amount of time spent with their children, the migration decision is an extensive margin choice of being either present in the child's life or temporarily migrating away and drastically increasing the households income. This provides the researcher with a clean measure of parental time input for both the mother and father depending on their respective migration decisions. It would also be reasonable to expect that the size of any observable impacts parental time input decisions may have to be much larger at the extensive margin compared to the intensive margin, thus allowing the impact of time inputs to be quantified more easily.

The second greatest challenge in estimating the CAPF and EPF is that inputs such as parental time and monetary investments are endogenous. That is, the causal impact of inputs in producing cognitive skills are confounded by unobservable variables that are correlated with both the cognitive skills and the inputs. Although instrumental variables have been the go to solution to address issues of endogeneity, the literature has struggled to come up with instruments for parental time input. At best, weak instruments have been used and the rigorous analysis of longer panel data, which requires an instrument for each period, has been impossible so far due to the lack of having enough instruments. In this paper, because the decision of parental time input at the extensive margin is synonymous with the migration decision when estimating the EPF in the context of migration I am able to utilize my novel gender-specific instrument for the migration decision to address the endogeneity of the parental time input decision. This paper therefore contributes to the CAPF and EPF literature by providing well identified causal estimates of maternal and paternal time inputs at the extensive margin for 6-11 year old children, something that particularly complements early childhood development (ECD)

literature estimates of CAPF production functions for children aged 0-5.

*Insert paragraph on summary of the results of the paper here (when you get them)*

In sum, this paper pushes the frontier of two important literatures; (i) the impacts of temporary migration on LBC and (ii) the literature on human capital accumulation and estimation of a child's EPF and CPAF. Within the domain of the temporary migration literature this is the first paper to dissect the causal impact of temporary migration on the specific inputs into the child's EPF in order to understand its impact on the educational outcomes of children. This is achieved with the use of a never seen before data set and a novel gender-specific instrument for the migration decision. Moreover, a policy recommendation for an optimal path of migration timings to maximize child welfare is given during a time where spatial differences in wages are being more commonly exploited to raise the economic welfare of families in developing countries. This paper also builds on the EPF and CAPF literature by analyzing an EPF in an innovative setting that allows me to address the problems of endogeneity and measurement error. In doing so, well identified causal estimates of extensive margin maternal and paternal time investments are obtained, which complement findings from the ECD literature estimates of the EPF and CAPF.

The paper proceeds as follows. Section I provides a detailed history and background on the Filipino migration context and explains how the unique variation and circumstances provide the ideal dataset to estimate the cognitive skill production function. Section II provides a literature review on the child cognitive production function literature and the literature on the impacts of migration on the educational outcomes of children left behind. Section III provides details on the data set from the Philippines that I collected and used. Section IV presents the theoretical framework for child cognitive skill development. The factor model that will be used to measure the child's cognitive skill and parental investments is also discussed. Section V discusses the identification strategy, the assumptions required to estimate the model, and the estimation procedure. Section VI presents the estimates from our model and discuses their implication in the context of both migration as well as the general understanding of cognitive skill development. Section VII concludes.

## Existing Literature and Contributions

## The Filipino Migration Context & Data Collection

In this section I first describe the the Filipino Migration Context, which provides important information that justifies the data collection methodology and identification strategy that I will utilize. I then provide a concise summary of the data collection that was undertaken in order to obtain the novel dataset used in the estimation of this paper. Tables of descriptive statistics are then presented for the reader to grasp a sense of the migrants in the sample.

## 3.1 The Filipino Migration Context

**Government Agencies:**

OFWs constitute one of the largest overseas working populations in the world, with cash remittances from OFW's accounting for almost 10% of the Philippines' GDP. To protect this huge population of worker's 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 of 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 OFW's and their families.

To protect the rights of OFW's, 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 surrounding the working rights and contract characteristics for OFW's.[2] 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, which in particular includes binding minimum wages, is reflected in the historical over supply of OFWs relative to the demand for OFWs by employers abroad [McKenzie et al., 2014], particularly with non-professional degree occupations that do not require a full bachelor's degree. This is particularly important as an overwhelming majority of OFWs will 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 therefore often arises from the variation in the recruitment agency fees that must be paid.

**Recruitment Agencies & Migration Networks:**

To assist and regulate the matching of OFWs with prospective overseas employers, a highly developed network of "recruitment agencies" is used. A recruitment agency is an officially licensed agency that is vetted rigorously by the POEA and has branches in various migration destination as well as corresponding satellite offices spread across the Philippines. Any overseas employer that wishes to employ an OFW first submits 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 contracts requirements, and act 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 then travel abroad for their employment opportunity.

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

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 risk that is associated with migrating. 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 the formal networks created by the recruitment agencies. This more formal migrant origin to migration destination network arises because the recruitment agencies will usually specialize and cater to specific occupation categories in a specific migration destination and have offices in distinct locations in the Philippines. This notion is supported by evidence from focus group discussions conducted prior to data collection where an overwhelming majority of Filipino migrants 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 (i) the ability to work for a higher wage abroad and, (ii) 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, PSA, 2016].[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 (FB). With more than a 90% penetration among Filipinos who do have access to the internet and the fact that messaging via Facebook Messenger (FBM) does not consume pre-paid data on their phone plans, FBM is the predominant way by which Filipinos communicate with each other [Chua, 2021, Malig, 2021]. In particular, FBM is practically used by every OFW to communicate and stay in touch with their families. Due to the deep entrenchment of FB usage the OWWA, POEA, and major OFW news and media outlets often disseminate important messages and information through their social media platforms.

## 3.2 Data Collection Overview:

Data collection can be broken down into primary and secondary data collection. Primary data collection constituted of collecting a novel ***retrospective*** panel of data from 2015 – 2022 on a sample of 1103 migrant families that contained a total 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 that 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 novel administrative data from the Philippines Department of Education (DepEd) for the outcome variable of all children in the migrant families, which was then linked to the primary data. Furthermore, a detailed panel of administrative data on all job contracts offered to migrant workers from the Department of Migrant Workers (DMW) and Philippines Overseas Employment Administration (POEA), and data from the occupational wages survey conducted Philippines Statistic Authority (PSA) was collected in

[3]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 that work in micro and small establishments.

order to construct the instrumental variables.

## 3.3 Primary Data Collection:

Primary data collection can be broken into three main stages:

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

**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 survey. Specifically, I cannot filter for eligible migrants and use the contact information that is contained in OWWA and POEA databases for the purposes of my survey. Instead, I had to create my own sample frame by gathering basic information, consent, and contact information on a representative sample of all OFW's and subsequently filter and recruit eligible migrants into the survey.

The sample frame from which I collect data from, is a representative sample of the population of all OFWs. The population of interest for this study is a subsample of the population of all OFWs. Given the Filipino Migration Context, I believe that the migrants who (i) currently follow/like official POEA, OWWA, and major OFW news and media FB pages, (ii) are in the databases of the OWWA and POEA, and (iii) are currently departing as an OFW in the airport or returning to the Philippines as an OFW, will form a representative sample of all OFWs both abroad and in the Philippines. I therefore create my sample frame by collecting data on OFW's and their families through a short 5-10 minute self-administered FBM chatbot hosted by the company Chatfuel. To encourage survey participation in this initial self-administered survey the communications team at the International Labour Organisation (ILO) and International Organisation of Migration (IOM) worked closely together with me to create branded promotional material that was subsequently distributed by the following means:[4]

1. The social media teams of OWWA, POEA and major OFW news and media outlets regularly posted the promotional material on all their available social media channels.
2. The Philippines Overseas Labour Offices (POLOs) stationed at each of the 32 major migration destinations of OFWs regularly posted the promotional material on all their social media channels.
3. Text messenger blasts containing the promotional material was sent to all migrants in the OWWA and POEA databases.
4. The POEA physically distributed promotional material to departing migrants by it attaching it to the cover of the OFW handbook, a handbook that is distributed to all departing OFWs at five our of the

[4]For examples of the promotional material, please refer to Appendix A.

eight international airports. A tarpaulin with the same promotional material was permanently set up at these location as well.

5. The OWWA physically distributed promotional material to returning migrants as they waited for transport to hotel quarantine facilities. A tarpaulin with the same promotional material was permanently set up at these main bus terminals as well.

The sample frame consists of all OFWs who responded to this promotional material, completed the self-administered FBM survey, and have consented to being contacted for a follow up phone survey. The basic characteristics of the OFWs in the sample frame are compared to the basic characteristics of the entire population of OFWs given by the DMW's administrative dataset (described in further detail below) .

**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. Of those migrants randomly drawn into the phone survey, 71% of these migrants responded and completed the 45-60 minute migrant phone survey. Subsequent to the completion of the migrant phone survey the same enumerator was tasked to also conduct the 45-60 minute phone survey with the migrant's household for which there was a 81% phone survey completion rate. The migrant phone survey collected detailed data on the employment history of the primary migrant of the household, including comprehensive information on the wages, occupation, days and hours worked, costs to migration, migration destination, and remittances. The household phone survey obtained comprehensive information on expenditures on the child and general household, savings, investments, assets, liabilities, health of the household members, and employment history of the household members that included information on the monthly location of each household member throughout the retrospective panel.

## 3.4 Secondary Data Collection:

Secondary data collection revolved around the collection of administrative data from three main sources: (1) Philippines Department of Education (DepEd), (2) Department of Migrant Workers (DMW), (3) Philippines Statistic Authority (PSA).

**DepEd Administrative Data Collection**

I jointly worked with the Philippines Office of the Innovations for Poverty Action (IPA) since August of 2019 to secure an unprecedented data sharing agreement (DSA) with the DepEd. The DSA was officially signed in February 2022. This DSA permitted unrestricted access to de-identified administrative data from the DepEd on every child that has attended school in the Philippines. This allowed me to link the administrative data on any child's academic outcomes of interest to data collected on the migrant and their household. To track and measure the academic outcome and performance of the children these measures need to be invariant to the age of the child and nuances that may arise from children attending different schools. To this end, I collected a panel of administrative data from the DepEd from the following two sources: (1) The Centralized Learner Information System (LIS), (2) The Bureau of Education Assessment (BEA).

***I also collected data directly from the Schools of each child, however this data was not used in the JMP. I assume I should therefore omit this detail (and the following paragraph) from the JMP? I only collected data in this way for approximately 20% of the children before funding ran out***

Data Collection From Schools:

Every child in the Philippines that attends school has their quarterly academic grades for each school subject, school attendance, and behavioral statements for the school year recorded in their annual school report (SF9) and their permanent school record (SF10). Detailed daily school attendance is recorded in School Form 2 (SF2). This information is recorded from the very first day any given child attends school in the Philippines. We will be collecting this information from Grade 1 until the current grade the child attends. In the case that the child was not currently enrolled in school, I obtain the records up to the last day the child attended school.

Orientation meetings regarding the data collection process for these school forms were been conducted with all 16 Regional Offices and 223 School Division Offices who have then subsequently conducted orientation meetings with each school in their Division to secure the cooperation of every school across the nation of Philippines. Each school subsequently scanning SF2, SF9, and SF10 for every child of interest and uploaded this data to a a secure encrypted Box folder. If the school was not able to electronically send the information, a hard copy of this data was be sent via postage to the IPA. This data was then subsequently encoded and linked to the phone survey data we have collected.

Learner Information System:

The LIS, a centralized electronic database housed at the central office of the DepEd in Manila, holds information on every child for every academic school year (starting from 2014) that the child was enrolled in school from Grades 1 - 10.[5] Of the 2904 biological children belonging to the 1103 migrant families, 2412[6] of these children were either above the age of five and therefore had started school and therefore have administrative data on the, or were young enough that the they were still enrolled in school in 2014 in Grade 10.

From the LIS, I collect the final arithmetic average score over all age standardized compulsory school subject tests administered throughout an academic school year for each biological child of the migrant in the migrant's household, for every school year these children were enrolled in school. I also collect the same final score for all children in the same grade of the school of the child. The final scores of the child's peers were obtained without any other personal identifying information to ensure data collection abided with the DSA and data privacy laws.

The outcome variable of this paper's headline result utilizes the following standardized test score:

$$Y := \frac{\text{Child's final score} - \text{Mean of final score for all children in the same grade}}{\text{Standard deviation of final score for all children in the same grade.}}$$

This standardized test score, provides an intuitive outcome variable that allows the reader to understand how

[5] Technically information is held for Grades 1 - 12. However for senior high school (grade 11 and 12), academic grades are not available in the LIS.

[6] ***Where should I talk about the number of children used for the estimates? And how should I talk about this in the paper. Currently I only have data on 1623, and I may not necessarily get the remainder of the data in time?***

well a given child of interest is doing relative to their peers and how much they may progress or regress compared to the peers as they develop each year as parental inputs vary. Moreover, such standardized scores often provide a good intuition to later life socio-economic outcomes. As the final average scores reported are age standardized, a robustness check for the results is also done using the reported score without the above standardization. To convince the reader that the reported scores are indeed age standardized, an additional panel of data from 2014 - 2022 on the average final score over each school grade from grades 1 - 10 for each school was collected. In the appendix[7], I show that over time and over grades this average does not change significantly, indicating the reported scores are indeed age standardized. As an ultimate robustness check, I also utilize National Achievement Test (NAT) data obtained from the BEA.

Bureau of Educational Assessment:

The BEA is responsible for annually administering the NAT to all grade 3, 6, 10, and 12 children nationwide. The NAT is a nationally age standardized test that was administered up until the COVID-19 pandemic. From the BEA, I obtained all available NAT score data for each child in my sample. For example, if a child was in grade 7 in school year 2019, I would obtain the NAT test scores when the child was in grade 3 in 2015 and grade 6 in 2018. A final robustness check of my findings is carried out with the subsample of children that had two or more observations of NAT scores throughout the time of the panel.

#### DMW Administrative Data Collection

Because of the role that the DMW performs, the DMW (previously POEA) has detailed data on every approved overseas job order that is made available to OFW's. 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 if they are to accept the offer such as the migration destination, wages, contract length, occupation, deployment date, and gender of worker requested. From the job offers that are accepted, I also am provided additional key information on the characteristics of every OFW that has successfully accepted and migrated abroad for a given job offer such as the migrant's age, gender, education level (from 2018 onwards), and origin location in the Philippines. The DMW and POEA have kindly shared a month by month panel of this data from January of 2010 until June of 2022.

#### PSA Occupational Wages Survey

Average occupation specific wage data across the Philippines was obtained from the occupational wages survey from the Philippines Statistic Authority.

## 3.5 Descriptive Statistics

[7] Should this be appendix material or should I insert the graph here.

# Theoretical Framework

## 4.1 Modelling the Migration Decision

I adapt a dynamic three period life cycle model to a migrant household. Each period the household receives utility from consumption and how well their child(ren) do at school. The household does not receive utility from how well the children do beyond the completion of secondary education. The household will incur disutility $D_m$ and $D_p$ whenever the mother or father migrates and spends time away from the household, where the subscripts $m$ and $p$ refer to maternal and paternal respectively. I assume that parents cooperate and act in the best interests of the household and their children.

Each period, the household chooses consumption $C$, savings $S$, and fraction of time each parent wants to stay at home, $\tau_m$ and $\tau_p$, normalized to $[0, 1]$. The observed number of months that a parent will be away from home is denoted by $T_m$ and $T_p$, where:

$$T_m = \tau_m + \delta_m \frac{1}{Q_m} \mathbb{1}\{\tau_m < 1\} \qquad \text{and} \qquad T_p = \tau_p + \delta_p \frac{1}{Q_p} \mathbb{1}\{\tau_p < 1\}. \tag{1}$$

$Q$ is the exogenously determined period and gender specific foreign labour demand for the parent's occupation measured in tens of thousand's of foreign contracts made available to OFW's in the same occupation as the parent. Once a migrant has chosen to work abroad, represented by $\mathbb{1}\{\tau_m < 1\}$, the migrant will incur a waiting time $\delta_m \frac{1}{Q_m}$ between when they applied and when they were deployed abroad, which is decreasing in $Q_m$. That is, the greater the foreign demand for a parent's occupation, the less time they will have to spend at home and wait earning a lower wage. If the mother chooses to migrate abroad to destination $d$ they will earn wage $W_{md} > W_{mh}$, where $W_{mh}$ is the wage if the mother were to stay at home instead. Similarly, I also assume $W_{pm} > W_{pd}$ for the father's wages. Migrating away therefore allows the household to potentially increase $C$ and $S$. In addition, in the first two periods the parents may choose an amount $M$ to invest into their children's education. An increase in $M$ will increase the next periods utility by enhancing the children's educational outcomes. However, the opportunity costs of migrating is the decrease in the time inputs of the mother and father, $T_m$ and $T_p$, which enter the child's education production functions $h_{\mathrm{y}}$ and $h_{\mathrm{o}}$, and the migration costs $K_m$ and $K_p$ incurred.

The education production functions $h_{\mathrm{y}}$ and $h_{\mathrm{o}}$ reflect the potential differences in the structural parameters of a "younger" and "older" child's education production function as the optimal amount and type of parental investments needed by children may differ by age. For a child $j$ in the household between the ages of 6 and 10 in period $t$, the child's educational outcome is defined to be:

$$Y_{jt} := h_{\mathrm{y}}\left(Y_{jt-1}, T_t, M_{jt}\right) + \Gamma_j + \varepsilon_{jt}, \tag{2}$$

where $T_t := (T_{mt}, T_{pt}, T_{gt})$ is the vector of time inputs, $M_{jt}$ is the monetary investment made into the child at period $t$, $\Gamma_j$ is the child fixed effect, and $\varepsilon_{jt}$ time and child specific idiosyncratic shock. Similarly, I define the educational outcome for child $k$ in the household between the ages of 11 and 15 in period $t$ by:

$$Y_{kt} := h_{\mathrm{o}}\left(Y_{kt-1}, T_t, M_{kt}\right) + \Gamma_k + \varepsilon_{kt}. \tag{3}$$

The vector $T_t := (T_{mt}, T_{pt}, T_{gt})$ for $t = 1, 2$ represent the final observed vector of times the mother, father, and grandparent presence in the household. As the primary focus of this paper is on parental migration and time investments, I assume that the presence or absence of grandparents $T_g \in \{0, 1\}$ in a household is predetermined. From data in my sample $T_g$ varies across the five year panel for only 3% of the households in my sample, and $XXX\%$ of these households have variation due to the death of a grandparent. In other words, $T_g$ is essentially a constant for an overwhelming majority of households and does not vary at all with the endogenous parental choice of $\tau_m$ and $\tau_p$ at all. This is confirmed by the descriptive regression **Insert the regression table of this below** below that regresses $T_g$ on $_m$ and $\tau_p$. Furthermore, regressing $T_g$ on the external instruments used in the estimation of the child's education production function shows what little observed variation $T_g$ across time for a household is indeed not explained by any of these external instruments.

I define $J_y$ and $J_o$ to be the number of younger and older children in the household in period one of the model, and the total number of children in the household to be $J := J_y + J_o$. Following evidence from the quantity-quality trade off literature of human capital investment I assume that parents care about the average educational outcomes of all of their children denoted by $Y_1, Y_2$, and $Y_3$ for periods 1, 2, and 3 respectively. Explicitly, $Y_1$ is the pre-determined educational outcomes of the child(ren) observed at the beginning of period 1, and $Y_2$ and $Y_3$ are respectively defined as:

$$Y_2 := \frac{1}{J}\left[\sum_{j=1}^{J_y} Y_{j2} + \sum_{k=1}^{J_o} Y_{k2}\right] \qquad \text{and} \qquad Y_3 := \frac{1}{J}\left[\sum_{j=1}^{J_y} Y_{j3} + \sum_{k=1}^{J_o} Y_{k2}\right], \tag{4}$$

In the second period, the $j = 1, ..., N^y$ children that were "young" in the first period are now "old". Thus for each $j$, $Y_{j3}$ is a function of $h_o$ and not $h_y$. Moreover, the $k = 1, ..., N_o$ children that were "old" in the first period are assumed to have now completed high school and no longer require parental investments of any kind. In the third and final period, the household will therefore receive utility from the updated educational outcomes of the $j$ "young" children $Y_{j3}$ which have completed high school in the third period, while receiving the same level of utility from the educational outcomes of $k$ "old" children where $Y_{k2} = Y_{k3}$.

Formally, the problem can be written as:[8]

$$\max_{\substack{C_1,\tau_{m1},\tau_{p1},M_1,S_1\\ C_2,\tau_{m2},\tau_{p2},M_2,S_2\\ C_3,\tau_{m3},\tau_{p3}}} \left\{ \begin{array}{c} U\left(C_1, Y_1, D_{m1}\left(\tau_{m1}\right), D_{p1}\left(\tau_{p1}\right)\right) + \beta \mathbb{E}\left[U\left(C_2, Y_2, D_{m2}\left(\tau_{m2}\right), D_{p2}\left(\tau_{p2}\right)\right)\right] \\ + \beta^2 \mathbb{E}\left[U\left(C_3, Y_3, D_{m3}\left(\tau_{m3}\right), D_{p3}\left(\tau_{p3}\right)\right)\right] \end{array} \right\} \tag{5}$$

subject to:

1. The budget constraint for period 1:

$$\begin{aligned} C_1 + M_1 + K_{m1}T_{m1} + K_{p1}T_{p1} + S_1 \leq\ & T_{m1}W_{mh1} + \left(1 - T_{m1}\right)W_{md1} \\ & + T_{p1}W_{ph1} + \left(1 - T_{p1}\right)W_{pd'1} \end{aligned} \tag{6}$$

2. The budget constraint for period 2:

$$\begin{aligned} C_2 + M_2 + K_{m2}T_{m2} + K_{p2}T_{p2} + S_2 \leq\ & T_{m2}W_{mh2} + \left(1 - T_{m2}\right)W_{md2} + T_{p2}W_{ph2} \\ & + \left(1 - T_{p2}\right)W_{pd'2} + (1 + r)S_1 \end{aligned} \tag{7}$$

[8] With the abuse of notation, as the household's problem is written below, $M_1$ and $M_2$ represent the vector of monetary investments being made into the children.

3. The budget constraint for period 3:

$$\begin{aligned} C_3 + K_{m3}T_{m3} + K_{p3}T_{p3} \leq T_{m3}W_{mh3} + (1 - T_{m3})\, W_{md3} + T_{p3}W_{ph3} \\ + (1 - T_{p3})\, W_{pd'3} + (1 + r)S_2 \end{aligned} \tag{8}$$

4. The children's educational outcomes in period 2 and 3 defined in eq. (4) above, where

$$M_1 := \sum_{j=1}^{J_y} M_{j1} + \sum_{k=1}^{J_o} M_{k1} \qquad \text{and} \qquad M_2 := \sum_{j=1}^{J_y} M_{j2} \tag{9}$$

Assuming that the utility function specifically takes on the functional form:

$$U\left(C, Y, D_m\left(T_m\right), D_p\left(T_p\right)\right) = \left(\theta_c + \zeta_c\right)\log(C) + \left(\theta_y + \zeta_y\right)\log(Y) - \left(\Psi_m + \zeta_m\right)T_m - \left(\Psi_p + \zeta_p\right)T_p, \tag{10}$$

where the constants $\Psi_m, \Psi_p > 0$ are the disutility that the mother and father receive and $\zeta_c, \zeta_y, \zeta_m, \zeta_p$ are multivariate normal distributed unobserved preference heterogeneity.

**Assumption 4.1.1.** *We assume that every family is a family that has both the mother and father and their biological children. We consider the household income to be only from the mother and father and do not count income from any extended family members.*[9]

**Assumption 4.1.2.** *I ignore extended family members and the migration history.*

# Identification & Estimation

In this section, I discuss the identification of the education production function followed by the estimation procedures that will be used to estimate both the structural model of the household and education production function of the child.

## 5.1 Identification Overview

From the theoretical framework above, the key endogenous choice variables from the household's optimization problem are parental time $T$ and monetary investments $M$ that enter into the child's education production function, which determine the child's educational outcomes $Y$ observed at the end of the current period. These key variables of interest are summarized in Table 1 below:

Table 1: Key Variables of Interest

| **Variable of Interest** | **Measurement/Data** |
|---|---|
| Academic Outcome ($Y$) | School test scores from DepEd admin data standardized across all their class peers. |
| Monetary Investments ($M$) | Budgeted annual expenditure for education and health reported by the primary caregiver of the child. |
| Time Investments/Migration Decision ($T$) | Number of months a person in the household is present in the child's life. |

The aim is to estimate a child's education production function that takes the following general functional form:

$$Y_{ijt} = h_0\left(Y_{ijt-1}, M_{ijt}, T_{ijt}\right) + \Gamma_{ij} + \varepsilon_{ijt}. \tag{11}$$

In this above equation $\Gamma_{ij}$ represents child $j$'s fixed effect and $\varepsilon_{ijt}$ is the standard time specific idiosyncratic shock experienced by the child. The inclusion of the lagged dependent variable, $Y_{ijt-1}$, allows for the child to build upon their previous levels human capital. This reflects evidence from prior literature such as Cunha et al. [2010], which suggests that there is a dynamic complementarity between past inputs that enter through last

[9]The only purpose of having extended family members is to provide an additional variable that is interacted with the terms in the migration decision function, which will provide household level variation for estimation.

periods accumulated human capital and current inputs.

Identification of the production function is plagued by three sources of endogeneity that are summarized in table 2 below. 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 and influence the endogenous choice of time and monetary investments 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 preferences of the child to learn and attend school. To exploit the power of the time series nature of the novel data I include $\Gamma_{ij}$, which absorbs this time invariant endogeneity resulting in the idiosyncratic shock $\varepsilon_{ijt}$ in eq. (18) to constitute only of the first two sources of endogeneity. However, the addition of $\Gamma_{ij}$ introduces Nickell bias over and above other biases that arise due to the regressors not being orthogonal to $\varepsilon_{ijt}$, especially with the inclusion of $Y_{ijt-1}$ [Nickell, 1981]. To accurately estimate $h_0$ and combat this endogeneity I utilize a panel of external instruments that are unique to the Filipino migration context in order to instrument for all three endogenous regressors: $Y_{ijt-1}, M_{ijt}$, and $T_{ijt}$.

Table 2: Sources of Endogeneity

| **Endogeneity** | **Source/Example** | Solution |
|---|---|---|
| Measurement Error | Retrospective panel data. | Instrumental variables |
| Time Specific/Varying Endogeneity | Sudden health shock to child, unexpected family death in household, unexpected 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 |

## 5.2 Instrumental Variables:

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 $\varepsilon_{ijt}$ which only contains the contemporaneous idiosyncratic shock as the child's education production function includes $\Gamma_{ij}$. Under the premise that the instruments for the parental investments are good instruments and parental investments causally impact the child's educational outcome significantly, something that will be shown in the results, the lagged panel of parental investment instruments will be trivially be a suitable set of instruments for the $Y_{ijt-1}$.

As discussed above in the theoretical framework, the time inputs of other family members is treated as predetermined in the child's education production function as they are beyond the scope of this paper. In the

results section I provide several robustness checks and show that time inputs from other family members are indeed uncorrelated with parental investment decisions and the corresponding instruments used for these investments. In what follows, I provide a detailed description and justification of the instrumental variables used for parental investments.[10]

**Parental Time Investments:**

Let $d \in \mathcal{D}$ be a migration destination where $\mathcal{D}$ is the set of all possible migration destinations, and $\ell_i$ be the origin in the Philippines of household $i$.[11] Define the historical migration network between $d$ and $\ell_i$ as:

$$\omega_{id} := \frac{\text{Number of migrants from } \ell_i \text{ that have migrated to } d \text{ from 2010 - 2014}}{\text{Total number of migrants from } \ell_i \text{ from 2010 - 2014}}. \tag{12}$$

Define the primary occupation of an individual as the occupation that the individual spends the most time in throughout the duration of the panel. For parent $p$ in household $i$, define $Q_{pdti}$ to be the number of contracts from migration destination $d$ made available to OFW's for the primary occupation[12] and gender of parent $p$ in household $i$ at time $t$. Define the instrument for parent $p$'s time investment at time $t$ as:

$$Z_{it,\text{time},p} := \sum_{d \in \mathcal{D}} Q_{pdti}\omega_{id} \tag{13}$$

In this migration context, the parental time investment into a child is equivalent to the decision to migrate. Whether or not parent $p$ is able to migrate is highly determined by the occupation and gender specific labour demand from prospective employers abroad at that point in time. If foreign labour demand, as measured by $Q_{pdti}$ increases for a specific occupation in a given year it will be more likely that a parent will also be able to migrate abroad for work. The relative impact a fluctuation in the country specific labour demand will have on the migrant's decision is further influenced by the historical migration networks a migrant has given their location $\ell_i$ in the Philippines. The stronger $\omega_{id}$ is, the greater the impact a given fluctuation or change in $Q_{pdti}$ will have on the migrant's propensity to migrate. To illustrate this, consider a migrant situated in a municipality in Bangsamoro Autonomous Region in Muslim Mindanao (BARMM), the autonomous region in the Philippines located in the southwest of Mindanao. Because Islam is the predominant religion here, recruitment agencies based in BARMM have formed much stronger migration networks with migration destinations in the Middle East as employers from these migration destinations have a strong preference for OFW's that have similar cultural backgrounds. Consequently, it is plausible that a labour demand shock that occurs in Kuwait will have a relatively larger effect on the ability of a migrant located in BARMM to migrate compared to a labour demand shock that occurs in Hong Kong. Furthermore, the gender specificity of the instrument $Z_{it,\text{time},p}$ provides additional exogenous variation to assist in the identification of whether the mother or the father is the migrate. This exogenous variation stems from the fact that many occupations are highly gender selective. For example, from the DMW's administrative dataset 97% of all OFW's who worked as a domestic worker were female while 98% of all OFW's who worked in a type of job that required physical labour were male. Thus, I believe that $Z_{it,\text{time},p}$ will be a good predictor of the time investment by parent $p$ in year $t$.

[10] Although the description below breaks the instruments down into two

[11] An origin will be defined at the municipality level. It is therefore possible that two households may be from the same origin $\ell_i$

[12] The primary occupation of the individual is the occupation that the individual spent the most time in throughout the duration of the panel.

A stronger than sufficient condition for $Z_{it,\text{time},p}$ to satisfy the exclusion restriction and be a suitable instrument for the time investments of parent $p$ is:

$$\text{Cov}\left(Z_{it,\text{time},p}, \varepsilon_{ij\tilde{t}}\right) = 0 \qquad \forall \tilde{t}. \tag{14}$$

It is plausible that the contemporaneous decisions of employers in a foreign country and therefore the total number of successfully submitted work contracts for overseas employment, as measured by $Q_{pdti}$, are uncorrelated with $\varepsilon_{ij\tilde{t}}$ for any $\tilde{t}$ that a individual household or child of interest may be exposed to. This is because $\varepsilon_{ij\tilde{t}}$ should most likely stem from child or household specific events at the migrant's household location $\ell_i$. One concern a reader may have is if an unobserved aggregate shock, such as an economic downturn in the Philippines, were to simultaneously affect a child's educational outcomes but also cause the Filipino government to push for more migration through negotiations with foreign countries thus causing a change in $Q_{pdti}$. To allay this concern, I include a time and country fixed effects in my robustness check.

The historic network weight $\omega_{id}$ is defined prior to the start date 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 weights is the fact that a stronger historic networks in a given origin $\ell_i$ may result in $\ell_i$ 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 $\Gamma_{ij}$ 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 these justifications, I believe it is reasonable to assume that eq. (14) holds. In summary, $Q_{pdti}$ is the time, occupation, and gender specific level of foreign labour demand shock that acts to pull migrants abroad. The relative differential exposure to such an exogenous shock is then dependent on a given migrant's origin due to pre-existing migrant networks established by recruitment agencies.

**Fix this section!!!! Refer to notes from the meeting with Mark** **Monetary Investments:**

Define the primary migration destination of an individual as the foreign country the individual has spent the most time in for work throughout the duration of the panel.[13] If the individual had never worked abroad before, then the "primary migration destination" of this individual is defined to be the Philippines. Denote the primary migration destination of parent $p$ in household $i$ by $d_{pi}$. Define $W_{td_{pi},\text{fx}}$ to be the average monthly wage across all individuals of the same gender and occupation as parent $p$ that are in destination $d_{pi}$ in the currency of $d_{pi}$ at time $t$. To illustrate this, suppose the mother's primary migration destination was Hong Kong and her primary occupation was domestic work. Then $W_{td_{pi},\text{fx}}$ would be the average monthly wage a female domestic worker in Hong Kong would earn in Hong Kong Dollars at time $t$. Denoting the average foreign exchange rate at time $t$ between location $d_{pi}$ and the Philippines by $\text{FX}_{td_{pi}}$, I define:

$$W_{td_{pi}} := W_{td_{pi},\text{fx}}\text{FX}_{td_{pi}} \tag{15}$$

Define the following instruments for monetary investments into a child at time $t$ to be:

$$Z_{it,\text{money},p} := W_{td_{pi}} Z_{it,\text{time},p} \tag{16}$$

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 occupation and gender specific average

[13] Only 2% of the migrants in my sample had worked in two or more different migration destinations.

wage in their primary migration destination $d_{pi}$, especially when they are physically present in location $d_{pi}$. By transitivity it would therefore be reasonable to surmise that $W_{td_{pi}}$ would be correlated with child expenditures, especially in the time periods where the parent is indeed in the primary migration destination $d_{pi}$. To capture the additional variation that occurs in wages when a parent is located in the Philippines and their wages are likely to be substantially lower compared to if they were abroad, I interact $W_{td_{pi}}$ with the parent's time instrument $Z_{it,\text{time},p}$. In doing so, I additionally capture the correlation of lowered wages when the parent is at home in the Philippines which likely occurs when there is lowered foreign labour demand and the parent is less likely to have migrated. Therefore, it is plausible to believe that the variable $Z_{it,\text{money},p}$ for both parents will be a good predictor for monetary investments into children at time $t$.

A stronger than sufficient condition for $Z_{it,\text{money},p}$ to satisfy the exclusion and be a suitable instrument for monetary investments into a child is:

$$\text{Cov}\left(Z_{it,\text{money},p}, \varepsilon_{ij\tilde{t}}\right) = 0 \qquad \forall \tilde{t}. \tag{17}$$

As the exogeneity of $Z_{it,\text{time},p}$ has already been rationalized above, I now advocate for the exogeneity of $W_{td_{pi}}$. In the case that $d_{pi}$ is the Philippines, by the definition and construction of $W_{td_{pi}}$ being the average wage amount nationwide across the Philippines, this ensures that there is no endogenous choice of the individual's wages at any time period. It is therefore plausible that the average wage of the parent's occupation are determined independently of the unobservable idiosyncratic shocks that effect the child's educational outcomes. In addition this reasoning, whenever the primary migration destination $d_{pi}$ is not the Philippines, due to the unique migration context of the Philippines,[14] the wages are essentially exogenously determined by laws, regulations and bilateral agreements. Moreover, time specific exchange rate fluctuations further ensure that there is sufficient exogenous variation in $W_{td_{pi}}$ to aid in the identification of child expenditures. The concern a reader may have regarding an aggregate shock to the Philippines that may effect both the occupation specific average wage amounts and a child's education outcomes is ameliorated by including time and country fixed effects in my robustness check. In summary, $W_{td_{pi}}$ could be interpreted as the time, occupation, and gender specific exogenous shifter of the household's income and thus child expenditures. The relative differential impact of such an exogenous shifter is then dependent on a the level of foreign labour demand at that time period.

### 5.3 Estimation

The aim is to estimate a child's education production function that takes the following general functional form:

$$Y_{ijt} = h\left(Y_{ijt-1}, M_{ijt}, T_{ijt}\right) + \Gamma_{ij} + \varepsilon_{ijt}. \tag{18}$$

The $\Gamma_{ij}$ represents child $j$'s fixed effect and $\varepsilon_{ijt}$ is the standard time specific idiosyncratic shock experienced by the child. The inclusion of the lagged academic outcome ($Y_{ijt}$) is to allow for the child to build upon their previous levels human capital. This reflects evidence from prior literature such as Cunha et al. [2010], which suggests that there is a dynamic complementarity between past inputs that enter through last periods accumulated human capital and current inputs. To exploit the power of the time series nature of the data, I include a child fixed effect in order to account for time invariant unobservables such as the child's innate ability or

[14] Refer to section insert correct section number: Filipino Migration Context

household/child preferences.

I assume the age specific EPF of the child takes on the following nested CES functional form:

$$Y_{ijt} = \left[\gamma Y_{ijt-1}^{\rho} + (1-\gamma)\left[\left(\alpha T_{ijt}^{\eta} + (1-\alpha) M_{ijt}^{\eta}\right)^{\frac{1}{\eta}}\right]^{\rho}\right]^{\frac{1}{\rho}} \exp\left[\Gamma_{ij} + \varepsilon_{ijt}\right], \tag{19}$$

$$Y_{ijt} = \left[\gamma Y_{ijt-1}^{\rho} + (1-\gamma)\left[\left(\alpha T_{ijt}^{\eta} + (1-\alpha) M_{ijt}^{\eta}\right)^{\frac{1}{\eta}}\right]^{\rho}\right]^{\frac{1}{\rho}} + \Gamma_{ij} + \varepsilon_{ijt}, \tag{20}$$

where $T_{ijt}$ is a CES aggregations of time inputs from the mother, the father and the grandparents:

$$T_{ijt} = \left(\beta_1 T_{ijt\text{mum}}^{\xi} + \beta_2 T_{ijt\text{dad}}^{\xi} + \beta_3 \left(T_{ijt\text{mum}} \mathbb{1}_{ijt\text{grandparent}}\right)^{\xi} + \beta_4 \left(T_{ijt\text{dad}} \mathbb{1}_{ijt\text{grandparent}}\right)^{\xi}\right)^{\frac{1}{\xi}}$$

The $K_\theta = 9$ dimensional vector of parameters of interest for the EPF is therefore:

$$\theta := (\gamma, \alpha, \rho, \eta, \beta_1, \beta_2, \beta_3, \beta_4, \xi).$$

# Results:

Orazio's suggestion of new production function specification. For child $j$ we have:

$$\begin{aligned}\log(Y_{jt}) := {} & (\gamma_{11} + \gamma_{12}\mathrm{MA}_t)\log \mathrm{Exp}_t + (\gamma_{21} + \gamma_{22}\mathrm{MA}_t)\log Y_{jt-1} + (\gamma_{31} + \gamma_{32}\mathrm{MA}_t)\log \mathrm{Exp}_t \log Y_{jt-1} \\ & + (\gamma_{41} + \gamma_{42}\mathrm{PA}_t)\log \mathrm{Exp}_t + (\gamma_{51} + \gamma_{52}\mathrm{PA}_t)\log Y_{jt-1} + (\gamma_{61} + \gamma_{62}\mathrm{PA}_t)\log \mathrm{Exp}_t \log Y_{jt-1} \\ & + \gamma_7\mathrm{PA}_t + \gamma_8\mathrm{MA}_t + \Gamma_j + \varepsilon_{jt}\end{aligned} \tag{21}$$

Table 3: Linear (Child) Fixed Effects Child Education Production Function Estimates

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Internal School Age Standardized Test Score | | | |
| | Age 6 - 10 Linear FE | Age 11 - 15 Linear FE | Age 6 - 10 Linear FE (IV) | Age 11 - 15 Linear FE (IV) |
| Grandparent (GP) Presence | 2.426* (1.430) | 1.095 (2.564) | 3.777* (2.082) | 0.025 (1.892) |
| Maternal Absence (Months) | −0.421*** (0.044) | −0.154*** (0.049) | −0.750*** (0.117) | −0.571*** (0.152) |
| Maternal Absence (Months) with GP | 0.245*** (0.058) | 0.122* (0.074) | 0.024 (0.174) | 0.007 (0.230) |
| Paternal Absence (Months) | −0.135*** (0.052) | 0.075 (0.056) | −0.402*** (0.127) | −0.284* (0.172) |
| Paternal Absence (Months) with GP | 0.102* (0.061) | −0.176** (0.084) | 0.354* (0.184) | 0.116 (0.279) |
| Educational Expenditures | −0.315*** (0.089) | 0.179 (0.120) | 1.151*** (0.373) | 2.750*** (0.453) |
| Lagged Test Score | −0.139*** (0.016) | 0.014 (0.024) | 0.161*** (0.060) | 0.356*** (0.112) |
| Observations (Child Year) | 5,017 | 3,371 | 5,017 | 3,371 |
| Number of Children | 1,792 | 1,216 | 1,792 | 1,216 |
| Child Fixed Effects | Yes | Yes | Yes | Yes |
| Residual Std. Error | 3.861 (df = 3365) | 5.409 (df = 2932) | 4.465 (df = 3328) | 6.277 (df = 2912) |

*Note:* *p<0.1; **p<0.05; ***p<0.01

Table 4: Linear Child Education Production Function Estimates: Without IV

Comparing Child Fixed Effects

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Internal School Age Standardized Test Score | | | |
| | Age 6 - 10 | Age 6 - 10 | Age 11 - 15 | Age 11 - 15 |
| | Linear FE | Linear FE | Linear FE | Linear FE |
| Grandparent (GP) Presence | 2.426* (1.430) | 0.162 (0.203) | 1.095 (2.564) | −0.415** (0.191) |
| Maternal Absence (Months) | −0.421*** (0.044) | −0.173*** (0.019) | −0.154*** (0.049) | −0.013 (0.019) |
| Maternal Absence (Months) with GP | 0.245*** (0.058) | −0.023 (0.026) | 0.122* (0.074) | 0.015 (0.031) |
| Paternal Absence (Months) | −0.135*** (0.052) | −0.029 (0.018) | 0.075 (0.056) | 0.011 (0.018) |
| Paternal Absence (Months) with GP | 0.102* (0.061) | −0.020 (0.026) | −0.176** (0.084) | −0.085*** (0.027) |
| Educational Expenditures | −0.315*** (0.089) | −0.025 (0.028) | 0.179 (0.120) | 0.051* (0.027) |
| Lagged Test Score | −0.139*** (0.016) | 0.863*** (0.007) | 0.014 (0.024) | 0.867*** (0.008) |
| Constant | | 12.756*** (0.805) | | 13.676*** (0.919) |
| Observations (Child Year) | 5,017 | 5,017 | 3,371 | 3,371 |
| Number of Children | 1,792 | 1,792 | 1,216 | 1,216 |
| Child Fixed Effects | Yes | No | Yes | No |
| Adjusted $R^2$ | | 0.775 | | 0.751 |
| Residual Std. Error | 3.861 (df = 3365) | 5.883 (df = 5120) | 5.409 (df = 2932) | 6.318 (df = 4286) |

*Note:* *p<0.1; **p<0.05; ***p<0.01

Table 5: Linear IV Child Education Production Function Estimates: Child Fixed Effects vs. No Child Fixed Effects

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Internal School Age Standardized Test Score | | | |
| | Linear FE (IV) Age 6 - 10 | Linear (IV) Age 6 - 10 | Linear FE (IV) Age 11 - 15 | Linear (IV) Age 11 - 15 |
| Grandparent (GP) Presence | 3.777* (2.082) | −3.362** (1.682) | 0.025 (1.892) | −1.506*** (0.564) |
| Maternal Absence (Months) | −0.750*** (0.117) | 0.095 (0.182) | −0.571*** (0.152) | 0.111 (0.070) |
| Maternal Absence (Months) with GP | 0.024 (0.174) | −0.176 (0.378) | 0.007 (0.230) | −0.178 (0.152) |
| Paternal Absence (Months) | −0.402*** (0.127) | 0.458 (0.289) | −0.284* (0.172) | 0.143** (0.071) |
| Paternal Absence (Months) with GP | 0.354* (0.184) | −0.030 (0.272) | 0.116 (0.279) | −0.068 (0.091) |
| Educational Expenditures | 1.151*** (0.373) | −0.522 (0.513) | 2.750*** (0.453) | −0.002 (0.120) |
| Lagged Test Score | 0.161*** (0.060) | −0.345 (0.458) | 0.356*** (0.112) | 0.591*** (0.085) |
| Constant | | 154.403*** (54.765) | | 47.289*** (10.516) |
| Observations (Child Year) | 5,017 | 5,017 | 3,371 | 3,371 |
| Number of Children | 1,792 | 1,792 | 1,216 | 1,216 |
| Child Fixed Effects | Yes | No | Yes | No |
| Adjusted $R^2$ | | −0.772 | | 0.669 |
| Residual Std. Error | 4.465 (df = 3328) | 16.494 (df = 5075) | 6.277 (df = 2912) | 7.276 (df = 4266) |

*Note:* *p<0.1; **p<0.05; ***p<0.01

Table 6: First Stage Regressions for Children Aged 6 - 10

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | Maternal Absence Grandparent | Paternal Absence Grandparent | Maternal Absence (Months) | Paternal Absence (Months) | Educational Expenditures | Lagged Test Score |
| Maternal Absence IV × GP | **2.350*** (0.269)** | −1.694*** (0.247) | −0.120 (0.273) | −0.234 (0.207) | 0.001 (0.052) | 0.360 (0.288) |
| Paternal Absence IV × GP | −1.338*** (0.416) | **2.339*** (0.411)** | 0.745** (0.330) | 0.345 (0.274) | −0.162 (0.099) | 0.797* (0.441) |
| Maternal Absence IV | 0.262** (0.118) | 0.623*** (0.117) | **3.042*** (0.245)** | 0.067 (0.173) | 0.141*** (0.050) | −0.960*** (0.263) |
| Paternal Absence IV | 0.860*** (0.193) | 1.342*** (0.210) | 0.144 (0.253) | **5.229*** (0.305)** | 0.287*** (0.100) | −1.427*** (0.371) |
| Maternal Wage IV | 0.421*** (0.071) | −0.039 (0.035) | 1.206*** (0.133) | −0.089* (0.049) | **0.319*** (0.042)** | −0.130 (0.084) |
| Paternal Wage IV | 0.066** (0.034) | 0.129*** (0.033) | −0.050 (0.044) | 0.278*** (0.061) | **0.152*** (0.043)** | 0.214*** (0.071) |
| Lag Maternal Absence IV | −0.143** (0.070) | 0.060 (0.046) | −0.546*** (0.086) | 0.166** (0.065) | 0.097*** (0.028) | **−1.993*** (0.216)** |
| Lag Paternal Absence IV | 0.094 (0.093) | −0.175*** (0.059) | −0.048 (0.100) | −0.457*** (0.069) | 0.266*** (0.040) | **−1.866*** (0.284)** |
| Lag Maternal Wage IV | 0.147*** (0.048) | 0.088*** (0.029) | 0.293*** (0.081) | 0.059 (0.042) | 0.045 (0.037) | **−0.021 (0.100)** |
| Lag Paternal Wage IV | 0.118*** (0.037) | −0.013 (0.025) | 0.180*** (0.044) | 0.054 (0.035) | 0.042 (0.041) | **0.374*** (0.095)** |
| Observations (Child Year) | 6,809 | 6,809 | 6,809 | 6,809 | 6,809 | 5,017 |
| Number of Children | 1,792 | 1,792 | 1,792 | 1,792 | 1,792 | 1,792 |
| KP F-Statistic | 18.12 | 13.41 | 39.85 | 45.01 | 12.4 | 12.33 |
| Child Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Residual Std. Error | 2.225 (df = 5503) | 1.632 (df = 5503) | 2.918 (df = 5503) | 2.178 (df = 5503) | 0.929 (df = 5503) | 4.584 (df = 3325) |

*Note:* *p<0.1; **p<0.05; ***p<0.01

Table 7: First Stage Regressions for Children Aged 11 - 15

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | Maternal Absence Grandparent | Paternal Absence Grandparent | Maternal Absence (Months) | Paternal Absence (Months) | Educational Expenditures | Lagged Test Score |
| Maternal Absence IV × GP | **2.462*** (0.306)** | −1.308*** (0.256) | −0.166 (0.323) | −0.020 (0.271) | −0.005 (0.068) | 0.313 (0.368) |
| Paternal Absence IV × GP | −0.876** (0.413) | **3.581*** (0.540)** | 0.530 (0.324) | 0.675 (0.432) | −0.078 (0.118) | −0.296 (0.532) |
| Maternal Absence IV | 0.424*** (0.109) | 0.567*** (0.109) | **3.367*** (0.277)** | −0.076 (0.202) | 0.158*** (0.055) | −0.965*** (0.291) |
| Paternal Absence IV | 0.641*** (0.163) | 0.962*** (0.203) | 0.348 (0.303) | **5.202*** (0.415)** | 0.219** (0.089) | −0.146 (0.389) |
| Maternal Wage IV | 0.229*** (0.065) | −0.004 (0.040) | 0.735*** (0.148) | −0.045 (0.044) | **0.300*** (0.026)** | −0.244** (0.096) |
| Paternal Wage IV | 0.026 (0.035) | 0.071* (0.037) | −0.052 (0.060) | 0.313*** (0.062) | **0.189*** (0.034)** | 0.048 (0.073) |
| Lag Maternal Absence IV | −0.192*** (0.070) | 0.010 (0.056) | −0.453*** (0.101) | 0.199** (0.083) | 0.123*** (0.039) | **−1.087*** (0.169)** |
| Lag Paternal Absence IV | 0.011 (0.077) | −0.176*** (0.062) | −0.086 (0.114) | −0.435*** (0.100) | 0.289*** (0.057) | **−1.071*** (0.264)** |
| Lag Maternal Wage IV | 0.112*** (0.038) | 0.044 (0.030) | 0.241*** (0.070) | −0.011 (0.041) | 0.100*** (0.034) | **0.442*** (0.095)** |
| Lag Paternal Wage IV | 0.070** (0.030) | 0.011 (0.033) | 0.113** (0.051) | 0.117*** (0.042) | 0.058* (0.030) | **0.695*** (0.105)** |
| Observations (Child Year) | 3,526 | 3,526 | 3,526 | 3,526 | 3,526 | 3,371 |
| Number of Children | 1,216 | 1,216 | 1,216 | 1,216 | 1,216 | 1,216 |
| KP F-Statistic | 15.62 | 12.97 | 25.18 | 36.64 | 21.36 | 11.26 |
| Child Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Residual Std. Error | 1.861 (df = 3166) | 1.545 (df = 3166) | 2.798 (df = 3166) | 2.161 (df = 3166) | 0.842 (df = 3166) | 4.917 (df = 3087) |

*Note:* *p<0.1; **p<0.05; ***p<0.01

Table 8: Replacing Child Expenditures with HH Income:

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Internal School Age Standardized Test Score | | | |
| | Age 6 - 10 | Age 6 - 10 | Age 11 - 15 | Age 11 - 15 |
| | Linear FE (IV) | Linear FE (IV) | Linear FE (IV) | Linear FE (IV) |
| Grandparent (GP) Presence | 3.761** (1.875) | 3.777* (2.082) | −0.951 (1.663) | 0.025 (1.892) |
| Maternal Absence (Months) | −0.792*** (0.122) | −0.750*** (0.117) | −0.711*** (0.190) | −0.571*** (0.152) |
| Maternal Absence (Months) with GP | 0.024 (0.170) | 0.024 (0.174) | −0.013 (0.256) | 0.007 (0.230) |
| Paternal Absence (Months) | −0.489*** (0.138) | −0.402*** (0.127) | −0.527** (0.214) | −0.284* (0.172) |
| Paternal Absence (Months) with GP | 0.343* (0.185) | 0.354* (0.184) | 0.024 (0.322) | 0.116 (0.279) |
| Household Income | 0.089*** (0.028) | | 0.271*** (0.050) | |
| Educational Expenditures | | 1.151*** (0.373) | | 2.750*** (0.453) |
| Lagged Test Score | 0.160*** (0.060) | 0.161*** (0.060) | 0.395*** (0.119) | 0.356*** (0.112) |
| Observations (Child Year) | 5,017 | 5,017 | 3,371 | 3,371 |
| $R^2$ | 0.916 | 0.915 | 0.817 | 0.832 |
| Adjusted $R^2$ | 0.871 | 0.870 | 0.731 | 0.754 |
| Residual Std. Error | 4.449 (df = 3328) | 4.465 (df = 3328) | 6.558 (df = 2912) | 6.277 (df = 2912) |

*Note:* *p<0.1; **p<0.05; ***p<0.01

Table 9: First Stage Regressions for Children Aged 6 - 10

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | Maternal Absence Grandparent | Paternal Absence Grandparent | Maternal Absence (Months) | Paternal Absence (Months) | Household Income | Lagged Test Score |
| Maternal Absence IV × GP | **2.350*** (0.269)** | −1.694*** (0.247) | −0.120 (0.273) | −0.234 (0.207) | −0.751 (0.635) | 0.360 (0.288) |
| Paternal Absence IV × GP | −1.338*** (0.416) | **2.339*** (0.411)** | 0.745** (0.330) | 0.345 (0.274) | −0.137 (1.380) | 0.797* (0.441) |
| Maternal Absence IV | 0.262** (0.118) | 0.623*** (0.117) | **3.042*** (0.245)** | 0.067 (0.173) | 3.728*** (0.543) | −0.960*** (0.263) |
| Paternal Absence IV | 0.860*** (0.193) | 1.342*** (0.210) | 0.144 (0.253) | **5.229*** (0.305)** | 8.657*** (1.216) | −1.427*** (0.371) |
| Maternal Wage IV | 0.421*** (0.071) | −0.039 (0.035) | 1.206*** (0.133) | −0.089* (0.049) | **4.787*** (0.363)** | −0.130 (0.084) |
| Paternal Wage IV | 0.066** (0.034) | 0.129*** (0.033) | −0.050 (0.044) | 0.278*** (0.061) | **2.261*** (0.407)** | 0.214*** (0.071) |
| Lag Maternal Absence IV | −0.143** (0.070) | 0.060 (0.046) | −0.546*** (0.086) | 0.166** (0.065) | 0.746** (0.324) | **−1.993*** (0.216)** |
| Lag Paternal Absence IV | 0.094 (0.093) | −0.175*** (0.059) | −0.048 (0.100) | −0.457*** (0.069) | 3.202*** (0.597) | **−1.866*** (0.284)** |
| Lag Maternal Wage IV | 0.147*** (0.048) | 0.088*** (0.029) | 0.293*** (0.081) | 0.059 (0.042) | 0.617 (0.398) | **−0.021 (0.100)** |
| Lag Paternal Wage IV | 0.118*** (0.037) | −0.013 (0.025) | 0.180*** (0.044) | 0.054 (0.035) | 0.373 (0.484) | **0.374*** (0.095)** |
| Observations (Child Year) | 6,809 | 6,809 | 6,809 | 6,809 | 6,809 | 5,017 |
| Number of Children | 1,792 | 1,792 | 1,792 | 1,792 | 1,792 | 1,792 |
| KP F-Statistic | 18.12 | 13.41 | 39.85 | 45.01 | 38.26 | 12.33 |
| Child Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Residual Std. Error | 2.225 (df = 5503) | 1.632 (df = 5503) | 2.918 (df = 5503) | 2.178 (df = 5503) | 10.371 (df = 5503) | 4.584 (df = 3325) |

*Note:* *p<0.1; **p<0.05; ***p<0.01

Table 10: First Stage Regressions for Children Aged 11 - 15

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | Maternal Absence Grandparent | Paternal Absence Grandparent | Maternal Absence (Months) | Paternal Absence (Months) | Household Income | Lagged Test Score |
| Maternal Absence IV × GP | **2.462*** (0.306)** | −1.308*** (0.256) | −0.166 (0.323) | −0.020 (0.271) | −0.350 (0.800) | 0.313 (0.368) |
| Paternal Absence IV × GP | −0.876** (0.413) | **3.581*** (0.540)** | 0.530 (0.324) | 0.675 (0.432) | 1.364 (2.056) | −0.296 (0.532) |
| Maternal Absence IV | 0.424*** (0.109) | 0.567*** (0.109) | **3.367*** (0.277)** | −0.076 (0.202) | 3.683*** (0.656) | −0.965*** (0.291) |
| Paternal Absence IV | 0.641*** (0.163) | 0.962*** (0.203) | 0.348 (0.303) | **5.202*** (0.415)** | 7.390*** (1.448) | −0.146 (0.389) |
| Maternal Wage IV | 0.229*** (0.065) | −0.004 (0.040) | 0.735*** (0.148) | −0.045 (0.044) | **3.300*** (0.338)** | −0.244** (0.096) |
| Paternal Wage IV | 0.026 (0.035) | 0.071* (0.037) | −0.052 (0.060) | 0.313*** (0.062) | **2.198*** (0.533)** | 0.048 (0.073) |
| Lag Maternal Absence IV | −0.192*** (0.070) | 0.010 (0.056) | −0.453*** (0.101) | 0.199** (0.083) | 1.285*** (0.418) | **−1.087*** (0.169)** |
| Lag Paternal Absence IV | 0.011 (0.077) | −0.176*** (0.062) | −0.086 (0.114) | −0.435*** (0.100) | 2.657*** (0.539) | **−1.071*** (0.264)** |
| Lag Maternal Wage IV | 0.112*** (0.038) | 0.044 (0.030) | 0.241*** (0.070) | −0.011 (0.041) | 1.269*** (0.365) | **0.442*** (0.095)** |
| Lag Paternal Wage IV | 0.070** (0.030) | 0.011 (0.033) | 0.113** (0.051) | 0.117*** (0.042) | 0.629* (0.358) | **0.695*** (0.105)** |
| Observations (Child Year) | 3,526 | 3,526 | 3,526 | 3,526 | 3,526 | 3,371 |
| Number of Children | 1,216 | 1,216 | 1,216 | 1,216 | 1,216 | 1,216 |
| KP F-Statistic | 15.62 | 12.97 | 25.18 | 36.64 | 20.29 | 11.26 |
| Child Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Residual Std. Error | 1.861 (df = 3166) | 1.545 (df = 3166) | 2.798 (df = 3166) | 2.161 (df = 3166) | 9.431 (df = 3166) | 4.917 (df = 3087) |

*Note:* *p<0.1; **p<0.05; ***p<0.01

Table 11: Determinants of Educational Expenditure

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | Educational Expenditures | | | | | |
| | Linear Fixed Effects with IV | | | | | |
| | Age 6 - 10 | Age 6 - 10 | Age 6 - 10 | Age 11 - 15 | Age 11 - 15 | Age 11 - 15 |
| Grandparent (GP) Presence | | | 0.020 (0.512) | | | −0.386 (0.350) |
| Maternal Absence (Months) | −0.037*** (0.011) | −0.043*** (0.015) | −0.043** (0.018) | −0.061*** (0.017) | −0.062*** (0.018) | −0.059** (0.025) |
| Maternal Absence (Months) with GP | | | 0.0004 (0.026) | | | −0.004 (0.030) |
| Paternal Absence (Months) | −0.071*** (0.012) | −0.084*** (0.016) | −0.082*** (0.022) | −0.103*** (0.018) | −0.108*** (0.018) | −0.097*** (0.027) |
| Paternal Absence (Months) with GP | | | −0.006 (0.030) | | | −0.026 (0.038) |
| Household Income | 0.076*** (0.004) | 0.080*** (0.006) | 0.080*** (0.006) | 0.101*** (0.007) | 0.102*** (0.007) | 0.102*** (0.007) |
| Lagged Test Score | | −0.0001 (0.010) | 0.0003 (0.010) | | 0.012 (0.014) | 0.012 (0.014) |
| Observations (Child Year) | 6,809 | 5,017 | 5,017 | 3,526 | 3,371 | 3,371 |
| Number of Children | 1,792 | 1,792 | 1,792 | 1,216 | 1,216 | 1,216 |
| Child Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Residual Std. Error | 0.730 (df = 5510) | 0.718 (df = 3331) | 0.718 (df = 3328) | 0.779 (df = 3173) | 0.786 (df = 3093) | 0.782 (df = 3090) |

*Note:* *p<0.1; **p<0.05; ***p<0.01

Table 12: Determinants of Educational Expenditures: Comparing IV with No IV

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Educational Expenditures | | | |
| | Linear FE (IV) Age 6 - 10 | Linear FE Age 6 - 10 | Linear FE (IV) Age 11 - 15 | Linear FE Age 11 - 15 |
| Maternal Absence (Months) | $-0.037^{***}$ (0.011) | $-0.014^{**}$ (0.007) | $-0.061^{***}$ (0.017) | $-0.025^{***}$ (0.007) |
| Paternal Absence (Months) | $-0.071^{***}$ (0.012) | $-0.043^{***}$ (0.007) | $-0.103^{***}$ (0.018) | $-0.050^{***}$ (0.007) |
| Household Income | $0.076^{***}$ (0.004) | $0.063^{***}$ (0.003) | $0.101^{***}$ (0.007) | $0.068^{***}$ (0.004) |
| Observations (Child Year) | 6,809 | 6,809 | 3,526 | 3,526 |
| Number of Children | 1,792 | 1,792 | 1,216 | 1,216 |
| Child Fixed Effects | Yes | Yes | Yes | Yes |
| Residual Std. Error | 0.730 (df = 5510) | 0.715 (df = 5638) | 0.779 (df = 3173) | 0.702 (df = 3193) |

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

Table 13: Grandparent Presence Regressed on IV's and Endogenous Regressors

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Grandparent Presence (Yes/No) | | | |
| | External IV's Age 6 - 10 | External IV's Age 11 - 15 | Endogenous Regressors Age 6 - 10 | Endogenous Regressors Age 11 - 15 |
| Maternal Absence IV | 0.005 (0.004) | −0.001 (0.001) | | |
| Paternal Absence IV | 0.010 (0.009) | −0.0004 (0.003) | | |
| Lag Maternal Absence IV | 0.0001 (0.001) | −0.0003 (0.002) | | |
| Lag Paternal Absence IV | 0.002 (0.004) | −0.0003 (0.004) | | |
| Maternal Wage IV | 0.001 (0.001) | −0.0001 (0.001) | | |
| Paternal Wage IV | 0.0001 (0.001) | 0.001 (0.001) | | |
| Lag Maternal Wage IV | 0.0002 (0.0003) | −0.0005 (0.0004) | | |
| Lag Paternal Wage IV | 0.00001 (0.001) | −0.001 (0.0005) | | |
| Maternal Absence (Months) | | | 0.001 (0.001) | −0.001 (0.001) |
| Paternal Absence (Months) | | | 0.001 (0.001) | 0.0003 (0.0003) |
| Educational Expenditures | | | −0.00001 (0.001) | 0.001 (0.002) |
| Lagged Test Score | | | 0.00005 (0.0001) | −0.0002 (0.0002) |
| Observations | 6,809 | 3,526 | 5,017 | 3,371 |
| Number of Children | 1,792 | 1,216 | 1,792 | 1,216 |
| Child Fixed Effects | Yes | Yes | Yes | Yes |
| Residual Std. Error | 0.049 (df = 5505) | 0.051 (df = 3168) | 0.046 (df = 3368) | 0.052 (df = 3113) |

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

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# Appendix A: Solving the Model

Formally, the problem can be written as:[15]

$$\max_{\substack{C_1,T_{m1},T_{p1},M_1,S_1\\ C_2,T_{m2},T_{p2},M_2,S_2\\ C_3,T_{m3},T_{p3}}} \left\{ \begin{array}{c} U\left(C_1, Y_1, D_{m1}\left(T_{m1}\right), D_{p1}\left(T_{p1}\right)\right) + \beta \mathbb{E}\left[U\left(C_2, Y_2, D_{m2}\left(T_{m2}\right), D_{p2}\left(T_{p2}\right)\right)\right] \\ +\beta^2 \mathbb{E}\left[U\left(C_3, Y_3, D_{m3}\left(T_{m3}\right), D_{p3}\left(T_{p3}\right)\right)\right] \end{array} \right\} \tag{22}$$

subject to:

1. The budget constraint for period 1:

$$\begin{aligned} C_1 + M_1 + K_{m1}\left(Z_{m1}\right) T_{m1} + K_{p1}\left(Z_{p1}\right) T_{p1} + S_1 \leq T_{m1} W_{mh1} + \left(1 - T_{m1}\right) W_{md1} \\ + T_{p1} W_{ph1} + \left(1 - T_{p1}\right) W_{pd'1} \end{aligned} \tag{23}$$

2. The budget constraint for period 2:

$$\begin{aligned} C_2 + M_2 + K_{m2}\left(Z_{m1}\right) T_{m2} + K_{p2}\left(Z_{p1}\right) T_{p2} + S_2 \leq T_{m2} W_{mh2} + \left(1 - T_{m2}\right) W_{md2} + T_{p2} W_{ph2} \\ + \left(1 - T_{p2}\right) W_{pd'2} + (1 + r) S_1 \end{aligned} \tag{24}$$

3. The budget constraint for period 3:

$$\begin{aligned} C_3 + K_{m3}\left(Z_{m1}\right) T_{m3} + K_{p3}\left(Z_{p1}\right) T_{p3} \leq T_{m3} W_{mh3} + \left(1 - T_{m3}\right) W_{md3} + T_{p3} W_{ph3} \\ + \left(1 - T_{p3}\right) W_{pd'3} + (1 + r) S_2 \end{aligned} \tag{25}$$

4. The children's education production functions in period 1 which will determine the children's educational outcome in period 2:

$$Y_2 = h_1\left(Y_1, T_{m1}, T_{p1}, T_{g1} M_1\right) + \Gamma + \varepsilon_1 \tag{26}$$

5. The children's education production functions in period 2 which will determine the children's educational outcome in period 3:

$$Y_3 = h_2\left(Y_2, T_{m2}, T_{p2}, T_{g2}, M_2\right) + \Gamma + \varepsilon_2 \tag{27}$$

Assuming that the utility function specifically takes on the functional form:

$$U\left(C, Y, D_m\left(T_m\right), D_p\left(T_p\right)\right) = \log(C) + \log(Y) + \left(\Psi_m + \zeta_m\right) T_m + \left(\Psi_p + \zeta_p\right) T_p, \tag{28}$$

we start in period 3 and solve for the optimal choices of $C_3, T_{m3}, T_{p3}$ conditional on the state variables and the prior endogenous choice variables being fixed. Define the vector of exogenously determined state variables:

$$\Omega_3 := \left(W_{md3}, W_{mh3}, W_{pd'3}, W_{ph3}, Z_{m3}, Z_{p3}, r\right) \tag{29}$$

Then given an arbitrary choice of $C_1, T_{m1}, T_{p1}, M_1, S_1, C_2, T_{m2}, T_{p2}, M_2, S_2$, this will pin down a $Y_3$, and the household will solve the maximization problem:

$$\max_{C_3,T_{m3},T_{p3}} \log(C_3) + \log(Y_3) + \left(\Psi_m + \zeta_m\right) T_{m3} + \left(\Psi_p + \zeta_p\right) T_{p3} \tag{30}$$

[15] With the abuse of notation, as the household's problem is written below, $M_1$ and $M_2$ represent the vector of monetary investments being made into the children.

subject to the constraint:[16]

$$C_3 + K_{m3}\left(Z_{m1}\right) T_{m3} + K_{p3}\left(Z_{p1}\right) T_{p3} \leq T_{m3} W_{mh3} + \left(1 - T_{m3}\right) W_{md3} + T_{p3} W_{ph3} + \left(1 - T_{p3}\right) W_{pd'3} + (1+r) S_2 \tag{31}$$

The corresponding Lagrangian for period 3 is given by:

$$\begin{aligned}\mathcal{L}_3\left(C_3, T_{m3}, T_{p3}, \lambda_3; Y_3, S_2\right) = & \log(C_3) + \log(Y_3) + \left(\Psi_m + \zeta_m\right) T_{m3} + \left(\Psi_p + \zeta_p\right) T_{p3} \\ & + \lambda_3 \Big[ T_{m3} W_{mh3} + \left(1 - T_{m3}\right) W_{md3} + T_{p3} W_{ph3} + \left(1 - T_{p3}\right) W_{pd'3} + (1+r) S_2 + W_Y\left(Y_3\right) \Big] \\ & - \lambda_3 \Big[ C_3 + K_{m3}\left(Z_{m1}\right) T_{m3} + K_{p3}\left(Z_{p1}\right) T_{p3} \Big]\end{aligned} \tag{32}$$

The corresponding first order conditions are:

$$[C_3]: \qquad \frac{1}{C_3} = \lambda_3 \tag{33}$$

...skip for now - get to period 2 (and this will help with period 3):

In period 2, the household has already chosen $C_1, M_1, T_{m1}, T_{m2}$ and $S_1$, which pins down $Y_2$.[17] The household faces the problem of choosing $C_2, T_{m2}, T_{p2}, M_2$, and $S_2$ in order to maximize period 2 utility as well as the optimized value function of period 3. Formally, the period 2 maximization problem can therefore be written down as:

$$\max_{C_2, T_{m2}, T_{p2}, M_2, S_2} \log(C_2) + \log(Y_2) + \left(\Psi_m + \zeta_m\right) T_{m2} + \left(\Psi_p + \zeta_p\right) T_{p2}, + \beta \mathbb{E}\left[V_3\left(\Omega_3, Y_3, S_2\right)\right] \tag{34}$$

subject to the budget constraint:

$$C_2 + M_2 + K_{m2}\left(Z_{m2}\right) T_{m2} + K_{p2}\left(Z_{p2}\right) T_{p2} + S_2 \leq T_{m2} W_{mh2} + \left(1 - T_{m2}\right) W_{md2} + T_{p2} W_{ph2} + \left(1 - T_{p2}\right) W_{pd'2} + (1+r) S_1 \tag{35}$$

and the child's education production function for $Y_3$:

$$Y_3 = h_2\left(Y_2, T_{m2}, T_{p2}, M_2\right) + \Gamma + \varepsilon_2 \tag{36}$$

Then substituting the second constraint eq. (36) into the value function, the corresponding Lagrangian for period 2 is:

$$\begin{aligned}\mathcal{L}_2\left(C_2, T_{m2}, T_{p2}, M_2, S_2, \lambda_2; Y_2, S_1\right) = & \log(C_2) + \log(Y_2) + \left(\Psi_m + \zeta_m\right) T_{m2} + \left(\Psi_p + \zeta_p\right) T_{p2} \\ & + \beta \mathbb{E}\left[V_3\left(\Omega_3, h_2\left(Y_2, T_{m2}, T_{p2}, M_2\right) + \Gamma + \varepsilon_2, S_2\right)\right] \\ & + \lambda_2 \Big[ T_{m2} W_{mh2} + \left(1 - T_{m2}\right) W_{md2} + T_{p2} W_{ph2} + \left(1 - T_{p2}\right) W_{pd'2} + (1+r) S_1 \Big] \\ & - \lambda_2 \Big[ C_2 + M_2 + K_{m2}\left(Z_{m1}\right) T_{m2} + K_{p2}\left(Z_{p1}\right) T_{p2} + S_2 \Big]\end{aligned} \tag{37}$$

[16] In period 3, the household only needs to choose whether or not someone should migrate in order to maximize their utility, as they are no longer investing into the child's educational outcomes (i.e. there is no $M_3$).

[17] The endogenous choice variables which pin down and provide sufficient information for the household to make an optimal decision in period two are $S_1$ and $Y_2$.

# Appendix A:

Examples of the promotional material that is created for social media promotion of this study.