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Essays on Family Choices in Developing Economies

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Declaration

I, Gina Andrade Baena, confirm that the work presented in this thesis is entirely my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis. Quotation from this document can be performed as soon as the source is fully acknowledged. The reproduction of this thesis or part of it is not permitted without prior permission of the author.

Abstract

Important gaps in knowledge remain when investigating the links between family characteristics and human capital investments along the life-cycle. Human capital formation (i.e. skills development) is problematic amongst low-income populations given the risk factors they are exposed to, such as poverty, malnutrition, non-stimulating home environments, and/or mistaken beliefs about returns to investments. Throughout three empirical chapters, this dissertation sheds light on the role of family characteristics and factors influencing two key human capital investments among deprived population in two developing economies: the choice of childcare and time allocation.

Chapter 2 examines childcare choices exploiting the experimental design of a scalable early childhood intervention in Colombia. Chapter 3 investigates the role of children's time use to produce one cognitive skill and two psychosocial skills; and the trade-offs of child work among alternative activities. Chapter 4 examines the relationship of birth order with time use and parental educational aspirations. The investigations in chapters 3 and 4 employ longitudinal data from Young Lives and focus on Peru. Furthermore, the analyses centres in three less documented life-stages within the human capital literature, childhood (ages 6-9), early adolescence (ages 10-14) and transition to adolescence (age 15).

Findings in chapter 2 indicate that the stimulation treatment led to an increase up to 4.6 percentages points in informal childcare relative to maternal care. I also find evidence of increases in maternal play time investments. Chapter 3 results show that time inputs effects are marginal for both types of skills, although daily time in educational activities is crucial for verbal development, specifically time spent studying and at school. Finally, in chapter 4, I find that being the second born sibling in two-child families has a significant and negative effect on child work; nonetheless, parents are equally likely to aspire for the highest level of education for both children.

Impact Statement

Overall, the topics investigated in this thesis have important implications to enhance our understanding of the human capital development process for disadvantaged children. In particular, it discovers important considerations to foster and enhance abilities for children since early in life. A consistent finding among the human capital literature is that differential investment along the life-cycle translate into variations or skill gaps, which in turns lead to inequalities in economic and social outcomes (Cunha, 2014). Investigating how to tackle these inequalities in the early years and how to foster and sustain skill development for deprived children allows for a fairer distribution of opportunities in life.

Findings in chapter 2 contribute to add on to the limited evidence on scalable[1] interventions in developing countries and to complement the growing literature documenting the importance of early childhood as a sensitive period for family investments in the child's development. Furthermore, the results document a potential methodological approach to test and examine parental decisions, while overcoming the inherent endogeneity on these decisions.

The results in chapter 3 provides significant evidence on the process of skill formation for other less documented life-stages along the human capital development cycle: childhood, early adolescence, and adolescence. Together, chapter 2 and chapter 3 provide evidence for most of the sensitive periods in the child's development process.

The analysis of time use, in both chapters 3 and 4, goes beyond the school enrolment and child work participation indicators, examining four different outcomes of daily time distribution, providing a more accurate reflection of the broader activities a child engages on a daily basis. Likewise, and distinct from previous work, I include domestic work as part of the child work definition. Analysis of the production and domestic work within the children's homes is imperative for appropriate policy-making that reflects prevalent circumstances in low-and-middle-income countries (Morrow & Boyden, 2018)

The present analysis also complements the meagre literature on the link between parental aspirations and household (individual) resource allocation decisions.

[1]Interventions designed and implemented using local infrastructure and human resources to save costs and reach a wider population. More details can be found in chapter 2.

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Chapter 1 Introduction

What drives human capital investment decisions? When do inequality gaps start to emerge and how do we tackle them? Which skills are more predictive of adult life success and what age is the most productive to foster them? These questions have long captivated the economics research community and a first pivotal step to answer them started around 60 years ago, with the concept of human capital. Nowadays, a renewed interest on how to foster skills and defining a core set of basic skills to succeed in life (i.e. levelling the field for disadvantaged[2] children) is fuelled by an international agenda[3], and policy awareness to tackle inequalities early on in the life-cycle.

The topics examined in this thesis relate to the growing literature documenting the process of skill acquisition (human capital) in mid-developing economies. Likewise, the following empirical chapters complement the studies trying to assess the role of two key factors on human capital development, the family and the child itself. Specifically, I investigate the family composition (e.g. two-child families) and investment choices along the child's life-cycle using both experimental and longitudinal data. For motivations to be clarified later, I emphasise the analysis within the context of economically disadvantaged children living in two large middle-income countries in Latin America, Colombia and Peru.

Despite economic growth within the Latin American region, persistent level of inequalities is a common trend among most of these countries. During the decade of sustained growth (2004-2014), various countries implemented active policies to combat poverty such as conditional cash transfers (CCT), and increased social expenditure, widening access to education and health. In this period, Latin America was the region that presented the most significant reductions in poverty (Inchauste et al., 2014). However, even with the excellent macroeconomic performance and poverty reduction, the highest rates of inequality in the region have fallen only moderately and continue to be among the highest in the world (de Ferranti, Perry, Ferreira, & Walton, 2004; Gasparini, Cruces, Tornarolli, & Marchionni, 2009; Herrera, 2017). This is true for the larger economies in the area including Mexico, Brazil, Chile, Colombia, and Peru. Another shared characteristic is the high number of school-age children engaged in child work. The prevalence of child labour is among the most high-profile policy

[2]In this thesis the concept of "disadvantaged" refers mainly to low-income population.
[3]The United Nations (UN), the United Nations Educational, Scientific and Cultural Organisation (UNESCO), the Organisation for Economic Co-operation and Development (OECD), and the World Bank (WB), all agree that the current and future educational agenda should be about skills. For instance, the UN in the 2030 Agenda for Sustainable Development established a set of Sustainable Development Goals (SDGs) relevant to skills and learning outcomes (e.g. the SDG4 aim is to "ensure inclusive and quality education for all and promote lifelong learning") (Nations, 2015). The latter was a major shift from goals completion related to inadequate and incomplete access to basic education, to now focus on delivering basic skills for all children (Rossiter, Woodhead, Rolleston, & Moore, 2018).

issues facing Lower-and Middle-Income Countries (LMIC). Within policy circles, there is a broad consensus that child labour is detrimental to child development. According to the International Labour Organization (ILO), in the period between 2004 and 2014, 57 LMICs implemented a total of 279 specific policies, plans and programmes aimed at reducing the prevalence of child labour (Keane, Krutikova, & Neal, 2018).

Skill development and, in general, human capital formation, is particularly problematic amongst deprived populations. Given their exposure to risk factors such as poverty, malnutrition and non-stimulating home environments, individuals from low income households typically underperform in later-life outcomes, delimiting their life trajectories and perpetuating an intergenerational persistence of poverty (O. Attanasio, Baker-Henningham, et al., 2018; M. Black et al., 2017). Earlier literature has stressed that the high levels of income inequality in Latin America, are strictly linked to inequality in educational achievement, which in turn is related to the gaps in early development (O. Attanasio et al., 2014; Azevedo & Bouillon, 2009). Fostering different types of skills among LMIC population early on (and along sensitive periods throughout the child's life-cycle) will help to reduce inequalities in the long run. Peru and Colombia offer an exceptional combination of characteristics to examine some of the dynamics in the process of human capital accumulation. It is crucial to understand and investigate this process within two country-contexts of high levels of inequality and among low-income population.

In Colombia, children and families in poverty represent close to 65% of the total population (Bernal, Attanasio, Peña, & Vera-Hernandez, 2018). There are 2.8 million children younger than 6 years-old living in poverty. From these poor children, 14% are stunted, and their scores in receptive language are one standard deviation below those of their peers in higher socioeconomic (SES) households (Bernal & Quintero, 2014). Among SES vulnerable children, aged 0–6 years-old, enrollment in public early childhood education programmes ranged from 20% to 40% for most of the period since the late 1980s (Bernal & Camacho, 2011). For a sample of children aged 6–42 months in low- and middle-income families in Bogota, Rubio-Codina, Attanasio, Meghir, Varela, and Grantham-McGregor (2015) demonstrated a SES gap of near 0.5 of a standard deviation in cognition and language between children in the top and bottom quartile of the within sample household wealth distribution. Gaps in fine motor and socio-emotional development were about half that size, whereas that in gross motor was not statistically significant. These gaps substantially widen with age for cognition and receptive language (Rubio-Codina, Attanasio, & Grantham-McGregor, 2016).

With an increasing interest in early childhood, the government launched in 2011 the national strategy *De Cero a Siempre* (From Zero to Forever), aimed at increasing access and improving the quality of early childhood services provided to poor children. The goal was to deliver high-quality and comprehensive early childhood services for 1.2 million disadvantaged children under the age of 6 with a budget close to USD 1,290 million per year over 4 years (Bernal et al., 2018; Bernal & Camacho, 2011).

There is one venue of research still fully unexplored related on how early childhood interventions could be implemented using available infrastructure, financial and local human resources to reach a wider population, and hence, forming the basis of realistic policy structure (O. Attanasio, Baker-Henningham, et al., 2018). The evidence on the effectiveness of scalable interventions is still scarce and inconclusive. However, Colombia has served as centrefield of unique scalable interventions testing. Using the infrastructure of the largest anti-poverty programme in Colombia, *Familias en Acción* (Families in Action), Attanasio et al. (2014) implemented a home visiting intervention, based on the successful curriculum Reach Up and Learn (S. Grantham-McGregor & Walker, 2015)[4], targeting families and children beneficiaries of this CCT programme. This intervention is the one examined in chapter 2. A few years later, Attanasio et al. (2018) implemented the same curriculum, but now using the structure of the Family, Women, and Infancy (FAMI) programme, a public large-scale parenting support services for vulnerable families in rural Colombia. Both interventions led to positive outcomes on the child's cognitive development and parental practices. In contrast, a recent study evaluated the transfer of children from home-based daycare services offered in the provider's own home to large purposely built and staffed with professionals childcare centres. They found no impact at a substantial cost (Bernal et al., 2018).

Investigations in chapters 3 and 4, draw on the same source of longitudinal data. Young Lives is a unique study of childhood poverty following the lives of 12,000 children over the past 15 years in four LMIC, Ethiopia, India (in the states of Andhra Pradesh and Telangana), Peru and Vietnam. In each country, the sample includes tracking two cohorts of children: a Younger Cohort, approximately 2,000 children, who were between 6 and 18 months old when Round 1 was collected (between January 2001 and May 2002); and an Older Cohort, about 1,000 children, who were between 7.5 and 8.5 years old. Chapters 3 and 4 focus on Peru, our country-case of interest, and use data from the Younger Cohort sample. In Peru, the sampling of the 20 clusters selected was at random, using districts as the unit sample frame. Then, within each cluster, 100 households with a child aged between 6 and 18 months were selected at random to participate in the study, excluding the wealthiest 5% districts. The attrition rate for Peru is low compared to other longitudinal studies, only 8.2% for the Younger Cohort from the first (2002) to the fifth (2016) round, for the unweighted panel (Espinoza-Revollo & Porter,

[4]This curriculum was first implemented in Jamaica. Following a continuous and documented success (e.g. large impacts on cognitive development and earnings 20 years later), similar structured curricula have been implemented in Bangladesh, Colombia, India, and Peru (O. Attanasio, Baker-Henningham, et al., 2018).

2018). Each Young Lives survey includes a child questionnaire, a household questionnaire, and a community questionnaire, collecting rich and detailed information at both individual and household levels, making it an exceptional resource for the present thesis. Peru is classified as a middle-income country. Since 1993, the Peruvian economy has doubled its GDP per capita. Between 2001 and 2015, the monetary poverty, which measures the proportion of the population that does not have resources to acquire a basket of essential goods and services, decreased from 55% to 22% (Favara & Sanchez, 2018). Several social programmes, including the large-scale CCT programme *Juntos*, were implemented during those years. Evidence from Young Lives confirms that household living standards improved significantly during that period.

Among the four countries in the Young Lives study, Peru is the one with the highest percentage of children participating in any type of paid work. Historically, Peruvian children do both, school and engage in child work, regardless of whether they live in urban or rural areas. Reflecting this reality, the Peruvian educational system has accommodated the duality of school and child work participation activities, given its organisation into part-time shifts (e.g. mornings and evenings) (Patrinos & Psacharopoulos, 1997).

Fostering psychosocial skills in childhood and early adolescence is important to reduce the high prevalence of risky behaviours when reaching adolescence. For Peru, an improvement of one standard deviation in Self-Esteem at the age of 15 is associated with a reduction of 7, 6 and 8 percentage points respectively in the probability of smoking, drinking and engaging in violent behaviours while drinking at the age of 19. Furthermore, Self-Esteem measured at the age of 12 is already a predictor of later drugs consumption, unprotected sex, criminal behaviours and the number of risky behaviours the adolescents engage with at the age of 19 (Favara & Sanchez, 2017). A cost-effective intervention designed to foster psychosocial skills, in particular, shifting the mentality of secondary Peruvian students to a "growth mindset" was *Expande tu Mente* (Grow your mind). The impact evaluation documented an increase in academic achievement among students at risk to drop-out, with the higher impacts observed in Lima (Outes, Sanchez, & Vakis, 2017).

An underlying conclusion of empirical research of human capital is that the process of skill development is sensitive to the investments made at different periods, to the choice of variables examined and to environmental macro and micro factors, such as the level of development of the country, region, village, access to schooling, among others. Hence, we recognise there is still much that we do not know.

Over the last decade, developments in the economics of human capital literature include extending the analysis of human capital from one dimension to multiple dimensions, and from one time-period, on which parents can compensate or reinforce, to multiple time-periods (i.e. life-stages) (Cunha & Heckman, 2007; Cunha, Heckman, & Schennach, 2010). Studies based on these extensions have improved our understanding of how skills develop over the life cycle; and provide a richer picture of schooling, skill formation along the life cycle, and earnings determination. These studies argue that fostering and accumulation of different abilities is a life cycle process. This means that throughout the different life stages (e.g. pre-birth, early childhood, childhood, early adolescence, adolescence up to adulthood), the accumulation and development of abilities is a dynamic and symbiotic process, product of different investments and inputs at each period, which in turn complements the future investments and stocks of distinct types of skills. Cunha and colleagues (2010, 2008, 2007, 2006) are the pioneers of this literature. They argue that different life stages represent critical and sensitive periods for investments aimed to foster skills. For sensitive periods, investments are especially productive; in critical periods, investments are essential. Critical and sensitive periods differ across skills and investments should target those periods (Cunha et al., 2010; Heckman & Mosso, 2014; Kautz, Heckman, Diris, ter Weel, & Borghans, 2014). Furthermore, the technology of skill formation that Cunha and Heckman (2007) developed recognises multiple skills: cognitive, psychosocial and biological skills (e.g. health) with a set of properties that allows a synergistic and interactive process along the life cycle between different types of skills (e.g. higher levels of psychosocial skills promote higher levels of cognitive skills) and investments.

In this line of research, a well-documented fact is that early childhood[5] is a sensitive period to promote child's development as in the first years of life human brain is particularly malleable. Investments during this period play a crucial role in the process of human capital accumulation (O. Attanasio, 2015; O. Attanasio, Cattan, Fitzsimons, Meghir, & Rubio-Codina, 2017; Knudsen, Heckman, Cameron, & Shonkoff, 2006). Likewise, the investments made at this stage lead to higher rate of returns and positive long-term effects for disadvantaged children (O. Attanasio et al., 2013; Barnett, 2011; F. Campbell et al., 2012; Cunha, 2014; Heckman, Moon, Pinto, Savelyev, & Yavitz, 2010; Hoddinott, Maluccio, Behrman, Flores, & Martorell, 2008; Olds et al., 2002). The same literature documents that child outcomes differences emerge from an early age (even before birth). Indeed, evidence looking at cross-sectional inequalities in different dimensions (such as cognition, health, socio-emotional skills) among individuals in various countries seem to emerge very early in life and appear to be strongly linked to inequality of human capital (O. Attanasio, 2015). Recent work by Molnár (2018) points to differential parental investments and differential time efficiency as important mechanisms behind widening skill gaps since early childhood. Investments in early child development can take many forms, including promotion of good health and nutrition, parenting support and early learning experiences (e.g. choice of childcare and preschool), and social sector investments

[5]From ages 0 to 5-years old.

(Britto et al., 2017; Özler et al., 2018). There is now increasing evidence that well-designed and targeted early childhood development interventions can alleviate inequalities in human capital investments and the negative consequences of detrimental factors in a long-lasting fashion, for both developed and developing economies. Examples include the Jamaica study (Gertler et al., 2014; S. Grantham-McGregor, Powell, Walker, & Himes, 1991; Walker, Chang, Vera-Hernandez, & Grantham-McGregor, 2011), the Perry Preschool program (Heckman et al., 2010) and the Abecedarian experiment (F. Campbell et al., 2014; F. Campbell & Ramey, 1994).

One key investment in early childhood is the choice on the type and quality of care. The type of childcare a kid experiences during this sensitive period may have important implications for their developmental trajectory and their family's well-being. It is crucial to understand how families end up in one type of childcare versus another, although there is limited evidence documenting this process (Bassok, Magouirk, Markowitz, & Player, 2018).

An aim of chapter 2 is to provide evidence on one scalable early childhood intervention conducted in Colombia. Using the infrastructure of the largest welfare programme *Familias en Acción*, the home visiting programme was implemented through a clustered randomised control trial (RCT) that lasted 18 months. The intervention delivered psychosocial stimulation and micronutrient supplementation to low-income families who were beneficiaries of *Familias en Acción*. The analysis on chapter 2 focuses on examining the psychosocial stimulation intervention, specifically, a parenting and family home-visiting programme, on their childcare choices between public, private and informal, relative to maternal care. This approach has not been tested before. The early childhood intervention exploited to investigate the impact in childcare choices combines unique features of experimental study design, scalability, home visiting, family support, and use of local resources. In addition, we probe to what extent the stimulation intervention affects three different time-investment outcomes measuring play time at home, and how these play time outcomes relate to the types of childcare observed at baseline.

Other sensitive periods for investment in human capital and skill development are childhood (ages 6-9), early adolescence (ages 10-14) and adolescence (ages 15-17). A strand of studies has examined various factors as determinants of skill formation, including family income, parental education, parental investments, quality of home environment and school's inputs, among others (Heckman, Pinto, & Savelyev, 2013; P. Todd & Wolpin, 2007). Not until very recent, there has been an increase in studies documenting both life stages as sensitive periods to foster psychosocial skills (Heckman & Mosso, 2014). Furthermore, this dynamic period of development is when health attitudes and behaviours and gender norms are shaped (Lane, Brundage, & Kreinin, 2017). According to Steinberg (2014), adolescence is a development process that needs to be nurtured, and where it is possible to minimise risky behaviours by building up on resiliency factors. Adolescents are very responsive to rewards and to reward-seeking behaviour and show reduced responsiveness to adverse stimuli such as punishment (Spear, 2013). The flexibility to adjust their behaviour has been suggested to be a crucial skill in enabling adolescents to understand and adapt to their changing social environment (Crone & Dahl, 2012).

Chapters 3 and 4 emphasise the analysis between childhood and transition to adolescence. In chapter 3, I investigate the role of children's time use to produce one cognitive skill (i.e. a verbal score) and two psychosocial skills (i.e. a Self-Efficacy index and a Self-Esteem index). Following a dynamic human capital accumulation approach (Cunha & Heckman, 2008), I estimate linear production functions for both types of skills. Under this framework, I combine time inputs, current and past, and lagged outcomes to examine the relevance of time investments made at younger ages relative to present time investments to produce three different outcomes by the time children reach 15 years old. The approach relates to the value-added literature in economics of education, employed to measure the role of school-level determinants (e.g. teacher effectiveness, class size, school autonomy) on educational achievement as function of various inputs and a lagged outcome (Dearden, Ferri, & Meghir, 2002 ; Jackson, 2018; Kane, Rockoff, & Staiger, 2008; Rivkin, Hanushek, & Kain, 2005; Sass, Semykina, & Harris, 2014). A second goal for this chapter is to investigate the trade-offs of child work among each alternative time input activity.

In chapter 4, I analyse the relationship of birth order with time use and parental educational aspirations for school-age children between 4-17 years old. I inspect the role of birth order in time investments, using extensive (school enrolment and child work binary outcomes) and intensive margins (continuous time use outcomes). I also investigate if parental aspirations vary by birth order, which might be one probable mechanism that might explain time use allocation.

As potential input or determinant for skill production, time allocation has received less attention, motivating the investigations in chapters 3 and 4. There are few empirical papers that study the role of time use on skill acquisition of children (P. Carneiro & Ginja, 2016; D. Del Boca, Flinn, & Wiswall, 2014; Fiorini & Keane, 2014; Hsin & Felfe, 2014; Nicoletti, Monfardini, & Del Boca, 2017). They have primarily focused on parental time, rather than the child's own time, and in developed countries settings.

Parental investments are one of the determinants of skill formation. These investments are made weighing numerous factors. Becker's seminal book *Treatise on the Family* (Becker, 1981) devises a theoretical model formalising the intra-household allocation of human and non-human capital investments across siblings. One of the main predictions of the model is that siblings with higher returns to human capital receive larger human capital investments. Hence, if returns to human capital investments are a function of the cognitive ability levels (Appleton, 2000; Becker, 1981), the model predicts that parents reinforce genetic differences in cognitive skills through allocating more human capital investments to more able siblings and compensate less endowed siblings with more non-human capital investments (Garcia-Hombrados, 2017). On birth order, most theories explaining intra-household resource allocation relying on the resource dilution model[6], predict negative relationships between human capital development and higher birth order (S. Black, Devereux, & Salvanes, 2005; Moshoeshoe, 2016).

I summarise my results as follows. Findings in chapter 2 show that the stimulation treatment led to an increase of up to 4.6 percentages points in informal childcare relative to maternal care. I also find evidence of increases in maternal play time investments (i.e. the number of activities). The results contribute to the literature by using for the first time the experimental study design of a scalable early childhood stimulation intervention to investigate parental childcare choices among four common types of care in the literature. The findings also contribute to add on to the limited evidence on scalable interventions in developing countries and to complement the growing literature documenting the importance of early childhood as a sensitive period for family investments in child's development.

The results in chapter 3 indicate that time inputs effects are small for both types of skills, although daily time spent in educational activities is crucial for verbal development, specifically time spent studying and at school, leading to an increase of up to 0.077 standard deviations by age 15. For the Self-Esteem Index, current time (at age 15) spent in leisure and past (at age 8) and current time spent in child work is detrimental for this skill at age 15, decreasing this outcome between 0.057 and 0.63 standard deviation, respectively. I highlight concerns on measurement error for the Self-Efficacy Index, excluding the results in the discussion. On the trade-off analysis of child work, I only find small detrimental effects for the verbal score of current time spent in paid work (at age 15), particularly when crowding-out time spent in educational activities; and no effects for the Self-Esteem Index. Some contributions on this chapter to the literature include confirming the evidence of the importance of time investments in education for cognitive skills and differences in malleability among each type of skills; and expanding on previous time use studies using Young Lives data (Borga, 2018; Keane et al., 2018) by including the latest survey round of data collection (Round 5). The latter allows

[6]The resource dilution model postulates that parental resources are finite and that as the number of children in the family increases, the resources accrued by any one child necessarily decline. Siblings are competitors for parents' time, energy, and financial resources and so the fewer the better (Downey, 2001).

reporting evidence on skill formation for other less documented life-stages along the human capital development cycle.

In chapter 4, I find that being the second born sibling in two-child families has a significant and negative effect on child work. The youngest sibling is 10.8 percentage points less likely to participate in child work and spending 0.81 hours (about 49 minutes) less in care activities of other household members. The results on child work are robust to differences in family size, observed endowments (birthweight and cognitive score), and families with "complete" fertility decisions. I found no conclusive evidence of birth order effects for school participation, time spent in educational activities (school or studying), and time spent in leisure. Notwithstanding the negative result between higher birth order siblings and child work, parents are equally likely to aspire for the highest level of education, a University/Postgraduate degree for both children. Among the contributions of this chapter to the literature, I can highlight that the analysis of time use goes beyond the school enrolment and child work participation indicators, examining four different outcomes of daily time distribution including hours spent at school, hours spent studying outside of school, hours spent in leisure activities, and hours spent in child work. This disaggregation complements findings from chapter 3 and recent work efforts using Young Lives data (Borga, 2018; Espinoza-Revollo & Porter, 2018; Keane et al., 2018). Distinct from this previous work, I examine how the distribution of different types of child work, including domestic work, relates to the birth order position of the child within the family. Analysis of the production and domestic work within the children's homes is imperative for appropriate policy-making that reflects local circumstances in LMIC (Morrow & Boyden, 2018). The analysis on chapter 4 also adds on to the scant literature on the link between parental aspirations and household (individual) resource allocation decisions.

Finally, chapter 5 summarises the main results of this thesis, outlining some policy implications. The final chapter also discusses the limitations of the present investigations and indicates future lines of research.

Chapter 2 Estimating the impact of an Early Childhood Parenting Programme on Childcare Decisions: Evidence from Colombia

2.1 Introduction

The variation in adult life outcomes is linked to differences in the environment that children experience in early years (O. Attanasio et al., 2013; Cunha, Heckman, & Navarro, 2005; Huggett, Ventura, & Yaron, 2011). A vast amount of studies following individuals from early childhood into adulthood from low-, middle, and high-income countries, show that children brought up in a more favourable early environment are healthier and taller, have higher cognitive ability and educational attainment, and earn significantly higher wages (Bouguen, Filmer, Macours, & Naudeau, 2018; Gertler et al., 2014; Havnes & Mogstad, 2011; Paxson & Schady, 2010; Walker, Chang, Powell, & Grantham-McGregor, 2005). Differentials in parental investments and their time efficiency are likely to play a role as essential mechanisms behind widening skill gaps since early childhood (Molnár, 2018). Economics and neuroscientific evidence pinpoint early childhood as a sensitive development stage for human capital investments. Indeed, early childhood research shows that investments made at this stage lead to higher rate of returns and positive long-term effects for socioeconomic disadvantaged children, helping to reduce inequality gaps in human capital (O. Attanasio et al., 2013; Barnett, 2011; F. Campbell et al., 2012; Cunha, 2014; Gertler et al., 2014; Heckman et al., 2010; Hoddinott et al., 2008; Olds et al., 2002). Whether and how the availability of early childhood programmes leads to positive outcomes for young children will also depend on parental investments responses in other dimensions, such as their choice for childcare. Because the type of childcare a child experiences during early childhood may have important implications for their developmental trajectory and their family's well-being, it is crucial to understand how families end up in one type of childcare versus another (Bassok et al., 2018).

There are considerable gaps in the literature on understanding parents' childcare choices even though research looking at childcare provision has increased due to the strong growth in the labour force participation of women with children (Elango, Garcia, Heckman, & Hofman, 2015; Felfe & Lalive, 2012). A contribution of this chapter is to look at the effect of a parenting programme on childcare choices among low-income parents exploiting the experimental design of an early childhood home-parenting programme in Colombia, an approach that has not been tested before.

The early childhood programme, implemented throughout 2010, was a clustered randomised control trial (RCT) that lasted 18 months. The target population for this study was children aged 12-24 months (n=1420) who were randomly allocated into three experimental arms: stimulation alone, micronutrient supplementation alone, both combined, and a control group. The overall aim of the intervention was to improve children's cognitive development, and a secondary aim was to reduce anaemia rates (O. Attanasio et al., 2014). The psychosocial stimulation treatment[7], our specific intervention of interest, included weekly home visits to promote child development, comprising intensive informational sessions on supporting and strengthening mother-child interactions, engaging families in play activities, centred on children's daily routines and using household resources, and overall stressing the importance of conducting child development activities throughout early childhood (O. Attanasio et al., 2017). Informational interventions in developing countries are important instruments that alleviate the inefficiencies of limited information and/or lack of knowledge among poor parents with the aim, in some cases, to alter behaviour. My hypothesis for the analysis is that the psychosocial stimulation treatment, besides promoting child development, might also impact parents' childcare decisions, as their knowledge and awareness increases regarding how to incentivise development for their children, and the importance of child development during early childhood for adult life outcomes. Experimental evidence has confirmed that providing information directly to parents in a clear and digestible way causes parents to update their beliefs and adjust their decisions accordingly (Dizon-Ross, 2018).

The main results in this chapter focus on evaluating the stimulation treatment impact on the choice of three mutually exclusive childcare categories, public, private and informal childcare, relative to maternal care. Two possibilities arise on how the psychosocial stimulation intervention affects childcare decisions. First, the intervention increases the child's skills, the increase in skills is observed by the parent, and this, in turn, induces a change in parental behaviour. The latter case is consistent with complementarity on investments and skills, central to the dynamic model of skill formation of Cunha and Heckman (2008). In most of the early childhood literature, parental investments (including childcare) are assumed to be made under perfect knowledge of the child's current skills as well as the technology that determines their law of motion. In reality, parent-child interactions are a developing system shaped by mutual interactions and learning (Cunha et al., 2010; Sroufe, Egeland, Carlson, & Collins, 2005). Second, the early childhood intervention delivered information on successful child development strategies (e.g. demonstrating activities) and their returns, thereby increasing parental knowledge (Cunha, 2014). As the stimulation treatment increased parents' knowledge on how to better take care of their kids, parents could reduce reliance on childcare. On the other hand, better knowledge of the importance of early stimulation and development reveals the potential long-term benefits of selecting "good" quality childcare. Parents could increase the demand for childcare, moving the child from informal childcare centres to more institutional

[7]Hereafter stimulation treatment or stimulation intervention.

childcare arrangements. Furthermore, childcare decisions might be influenced by other variables such as maternal labour participation or if within the household, another family member has knowledge or experience of child rearing (e.g. a grandparent).

A major lesson from early intervention research is that successful early childhood programmes tend to support child rearing, based on the premise that disadvantaged parents lack the information of “good” parenting practices, leading to positive gains in cognitive and development outcomes (Garcıa, 2015). The Colombian intervention was based on this premise, leading to positive effects on child development. A later study demonstrated that the developmental gains were due to increases in parental investments, improving the quality of the home environment[8] (O. Attanasio et al., 2017).

The impact of the stimulation treatment in childcare choices is estimated using a Multinomial Logit model. The evidence shows that the early childhood programme has no effect on most of the childcare options, except for a positive impact on informal childcare. The stimulation intervention increases, between 4.4 to 4.6 percentage points more likely to choose this type of care, relative to maternal care. The results are robust to alternative model specifications and adjustments on the child’s development level.

The analysis in this chapter also complements findings in Attanasio et al. (2017) in two ways. First, it confirms that the intervention led to increases in maternal time-investments related to play time, and second, it adds on the still limited evidence of scalable interventions in developing countries supporting deprived populations and implemented through pre-existing networks or infrastructures. On the first part, I investigate if the stimulation intervention affects three different time-investment outcomes measuring playtime at home, and how these playtime outcomes relate to the types of childcare observed at baseline. Interest in play time stems from its link with physical activity and child development in very young children (e.g. aged 0 to 5 years old), in turn associated with improvements in gross motor and fine motor skill development (Carsley et al., 2017; Stegelin, 2005). Understanding how playtime relates to childcare, and how early childhood interventions could improve overall playtime is important as part of the dynamics in the child’s development process and, as one proven channel that the stimulation treatment led to improvements in child development. I found some evidence that children in the stimulation group exhibit an increase in the number of play activities, in the play time factor index, and the total hours of play in any regular day, but unlike Attanasio et al. (2017), none of these impacts are statistically significant. Several reasons relate to the difference in these results including using different time use measures to identify effects, measurement error in the time use outcomes, and using different treatment and control groups

[8]The observed increases were in varieties of play materials and play activities, measured by a family care indicator developed by UNICEF (O. Attanasio et al., 2013; O. Attanasio et al., 2014).

comparisons.[9] Regarding baseline childcare, there are expected negative associations (large in magnitude and statistically significant) between being in any type of childcare different from maternal care and the three outcomes linked to play time at home. For the second part, it complements Attanasio et al. (2017, 2014) and a few scant studies (O. Attanasio, Baker-Henningham, et al., 2018; Gertler et al., 2014; Yousafzai, Rasheed, Rizvi, Armstrong, & Bhutta, 2014), on the use of scalable interventions implemented through pre-existing systems or infrastructures. The last feature has proven to reduce costs significantly, plus, these interventions might create more positive externalities in human capital development that the originals intended, as is the case of increasing informal childcare use.

The analysis proceeds as follows. Section 2.2 reviews the literature on early childhood interventions and childcare. Section 2.3 describes the intervention and data, and Section 2.4 outlines the methodology. Section 2.5 presents the results, while section 2.6 shows robustness exercises; and Section 2.7 discusses suggestive information regarding mechanisms. Finally, Section 2.8 concludes.

2.2. Related Literature

2.1.1 Importance of Early Childhood

The policy attention pointing to public investment in early childhood is fuelled by results from a large body of research highlighting the importance of early years (Currie & Almond, 2011; Heckman, 2008). Research suggests that for socioeconomic disadvantaged children, each $1 devoted to effective early childhood programmes in developing countries, leads to $2–$23 in future savings to investing localities and states (Bialik, 2012; Heckman, 2011). Early childhood interventions in developing countries are likely to be more effective if they are comprehensive (e.g. they include health, nutrition, and stimulation), run for longer, have greater intensity (e.g. higher frequency and longer duration of contacts), use a structured curriculum, and enable parents and children to participate together to practise stimulation activities and receive feedback (Engle et al., 2011; S. M. Grantham-McGregor, Fernald, Kagawa, & Walker, 2014; Yousafzai et al., 2014). Moreover, some of these early childhood interventions have used networks of existing social welfare schemes of large-scale programmes or health services already rolled out, generating substantial economies of scale and exploiting the experience of local human capital. This might be a promising approach to

[9] In the follow-up evaluation of Attanasio et al. (2014), investigating the mechanisms on how the stimulation treatment led to development gains, Attanasio et al. (2017) estimate the impact of the stimulation treatment by pooling the two groups that received it (stimulation and stimulation + nutrition groups) against the other groups that did not (only nutrition and control groups). I conduct as robustness test the same two group comparison and results are discussed in Section 2.4.

scaling up early childhood programmes in developing countries and one of the characteristics of the early childhood programme for the present analysis (O. Attanasio et al., 2014).[10]

Using this approach, a parenting training programme was integrated into primary health centre visits an implemented in three countries from the Caribbean (Jamaica, Antigua and St Lucia). The intervention had a significant benefit to children's cognitive development, with a treatment effect of 3.09 points (effect size = 0.3 standard deviations). Moreover, mothers in the intervention group improved significantly more in parenting scores than the control group (Chang et al., 2015). A study from Jamaica reports substantial effects on the earnings of participants in a randomised intervention conducted in 1986–1987 that gave psychosocial stimulation to growth-stunted Jamaican toddlers.[11] The authors re-interviewed 81 percent of study participants 20 years later and found that the intervention increased earnings by 25 percent, enough for them to catch up to the earnings of a non-stunted comparison group identified at baseline (Gertler et al., 2014). In a recent study based in Colombia, Attanasio et al. (2018) built on the Family, Women and Infancy programme (FAMI, for its acronym in Spanish)[12], to implement and deliver a structured early stimulation curriculum combined with a nutritional intervention. The aim was to increase children's development, maternal knowledge, maternal self-efficacy, and the quality of the home environment. Their intervention had a positive and significant effect on cognitive development (effect size = 0.15 standard deviations) and a reduction of 5.8 percentage points in the fraction of children whose height-for-age is below -1 standard deviations. These findings add to the evidence on the efficacy and effectiveness of community-based approaches to promote early childhood development in the first two years of life.

2.2.2 Childcare and parental choices

Much of the rising literature on childcare arrangements and child outcomes over the last few years has been influenced by the seminal work of Todd and Wolpin (2003) and Heckman and colleagues (P. Carneiro & Heckman, 2003; Cunha & Heckman, 2008; Cunha, Heckman, Lochner, & Masterov, 2006; Cunha et al., 2010). They modelled children's outcomes (e.g. cognitive, health and behavioural) as the result of a production function in which inputs are

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[10] Using the infrastructure of the CCT programme *FeA* and tapping on the network of local women (*Madres Lideres*), more details in Section 2.3.

[11] The intervention consisted of weekly visits from community health workers over a 2-year period that taught parenting skills and encouraged mothers and children to interact in ways that develop cognitive and socioemotional skills.

[12] The FAMI programme was first established in Colombia in 1991. It aims at improving pre and postnatal services for vulnerable pregnant women and their new born children up to the age two. The delivery is through weekly group meetings and one monthly home visit by a network of local women known as the FAMI mothers. For more information on FAMI see Attanasio et al. (2018).

provided by families as well as by other people and institutions (e.g. schools, teachers, peers, society) (D. Del Boca, Piazzalunga, & Pronzato, 2014).

There are three clear strands of research related to childcare. One is concerned with examining how attending childcare (and different types of childcare) affects child outcomes (e.g. development, skills, behaviour, among others). The quality of children's care has implications for their health, early social and human development, and later education and labour market success (Meyers & Jordan, 2006). The main challenge in this strand is to overcome endogeneity of parental selection into childcare, considering the alternative type of care the child would have used if she(he) has not attended childcare. To examine the effects of different types of childcare, researchers usually consider three alternatives: parental childcare, formal childcare and other, more informal sources of care (Blau & Currie, 2006; Drange & Havnes, 2015). In this line of research, evidence on the effects of childcare in the context of developing countries is still scarce. One study from Chile, using regional variation in the availability of childcare, found short-run gains from childcare targeted to children aged 5-14 months, particularly in motor and cognitive skills. They also document potential adverse effects in the areas of child-adult interactions, reasoning, and memory, raising awareness of the importance of securing quality when increasing childcare coverage (Noboa Hidalgo & Urzua, 2012).

The second field of childcare research focuses on looking at the effect of childcare on labour supply outcomes. For parents-as-providers, most often mothers, the price, availability, quality, and reliability of child care affect labour market attachment and hours of employment, particularly when children are young (Kimmel, 2009). Over the long term, mothers' employment accommodations for care giving have consequences for career advancement and earning trajectories, and for gendered wage and earning gaps (Meyers & Jordan, 2006). In countries where childcare services are scarce, and/or prices of private childcare are very high, families tend to rely on informal childcare provided by relatives. Previous studies have shown that the use of informal childcare, particularly grandparents, significantly increases mothers' labour participation, with stronger effects in disadvantaged families (Arpino, Pronzato, & Tavares, 2012; Posadas & Vidal-Fernández, 2012).

The third strand of research investigates which factors explain childcare decisions (i.e. childcare in the right-hand side of the equation). In this line of research, some studies examine the dynamic processes through which parents obtain and use information, evaluate their resources and alternatives, and reconcile competing concerns as parents and providers when arranging employment and childcare. These frameworks recognise that complex choices, as selecting a childcare arrangement, are rarely based on perfect information about preferences and alternatives, nor do they conform fully to traditional assumptions about cost/benefit optimisation. Three dimensions of parents' child care decisions provide particularly useful illustrations of how contextualised models of decision-making challenge traditional assumptions about individual rational choice: parents' a priori preferences and tastes for quality, parents' reliance on social networks for information, and parents' perceptions of available supply and resources for obtaining care. In a study looking at factors explaining childcare choices, Meyers and Jordan (2006) find that after controlling for household-economic factors, the household's social structure and the mother's language, child-rearing beliefs, and practices further help to predict the probability of selecting a centre-based programme. Children are more likely to be enrolled in a centre when the mother defines child rearing as an explicit process that should impart school-related skills (e.g. reading to her youngster, frequenting the library, teaching cooperative skills, and speaking English).

The analysis in this chapter fits within this last strand, where we take advantage of the unique identification framework the early childhood intervention provides. The primary goal of this chapter is to understand how childcare participation changes for children after parents, family and children, received the stimulation intervention. My exclusive focus upon the impact of the stimulation treatment arm is driven by both empirical and theoretical reasons. The empirical motivation follows that in Attanasio et al. (2014), where authors reported there were no significant impact in the micronutrient supplementation arm on any child developmental outcomes. In contrast, the stimulation treatment had a positive effect upon children's cognitive development (effect size = 0.26 standard deviations) and language scores (effect size = 0.22 standard deviations). The theoretical motivation relies on the design and implementation of the stimulation intervention, having an active component of parental education, teaching them how to engage in, and promoting development for their children.[13] This study relates to Attanasio et al. (2017) in the interest to understand the mechanisms behind the stimulation treatment and the observed developmental gains. The randomisation and the specific characteristics of the intervention, including the population of the study, the delivery mode (e.g. pre-existing networks), allows to single-out specific factors interacting within the complexity of household decisions. It might be the case that low-cost informational interventions could be a useful nudge tool to foster human capital investments (behaviours) throughout multiple channels even after they have finished.

[13]The stimulation with nutrition arm combined also included the parental education component. However, Attanasio et al. (2014) did not detect any significant effect in cognition in the interaction of stimulation with nutrition. Nevertheless, and following Attanasio et al. (2018), I estimate the stimulation treatment effect combining both groups as part of the robustness tests, the stimulation only and stimulation plus nutrition as the treatment group. More details in Section 2.5.2.

Overall, knowledge gaps remain on studies understanding the process of childcare decisions and the heterogeneous effects of different types of childcare. The next section describes the data used to measure the stimulation treatment effect on childcare outcomes.

2.3 Description of the intervention and data

2.3.1 Overview and recruitment

The analysis in this chapter draws on baseline and follow-up data from an early childhood home-parenting programme conducted in Colombia between 2010 and 2011 and lasting 18 months. The study design for the intervention was a clustered-RCT implemented in 96 municipalities (clusters) within Colombia using a 2x2 factorial design. The RCT included a control group and three treatment arms as follows:

i. A psychosocial stimulation
ii. A micronutrient supplementation (hereafter nutrition)
iii. Both psychosocial stimulation and micronutrient supplementation

The target population for this study was children aged 12-24 months resulting in a sample of 1420 children at baseline. A follow-up survey was conducted after treatment implementation (i.e. 18 months after) when children were now between 30 and 42 months old.[14] Main results for this study focus on examining how childcare decisions differ after receiving the stimulation treatment (i).[15] The stimulation intervention provided weekly home visits to mothers of the target children promoting child development by supporting and strengthening mother-child interactions. The visits also engaged families in play activities, centred around children's daily routines and using household resources (O. Attanasio et al., 2017). The treatment included modelling (e.g. demonstrating to the mother, different play activities and interactions to undertake with the child), scaffolding (e.g. instructing the mother in providing tasks that were at the developmental level of the child so as to be challenging but not too difficult), practice (e.g. encouraging the mother to exercise activities), and conditional positive reinforcement for both mother and child (O. Attanasio et al., 2013). An important feature of the stimulation treatment was that the home visitors were drawn from a network of local women generated by the administrative set-up of the CCT programme *Familias en Accion* (*FeA*). This CCT programme is the largest national welfare system in the country; it began in 2002 and targeted

[14]According to the authors of the study, 18 months was the maximum period covered by their funding and similar interventions have found sustainable benefits from interventions lasting from nine months to three years. When the target population reached their age at follow-up (i.e. between 30 and 42 months), children would be able to benefit from existing community care services (see Attanasio et al., 2014).
[15]The main analytic sample of the paper is for the 636 children at follow-up from the stimulation treatment arm and the control group. However, I also conduct robustness checks using the full sample by grouping the two treatment arms that received the stimulation treatment (e.g. stimulation alone and stimulation interacted with nutrition), and as control, I group the nutrition and control children together. More information on the sample size is provided in section 2.3.2.

the poorest 20% of households. Within *FeA*, every 50-60 beneficiaries periodically elect a representative who oversees the organisation of social activities and who acts as a mediator between them and the programme administrators. These women, known as *Madres Líderes* (MLs), are beneficiaries of the programme themselves. They are typically more entrepreneurial and proactive than the average beneficiary, influential and well connected in their communities. These characteristics marked them out as potentially effective home visitors (O. Attanasio et al., 2013). In each municipality, three MLs were randomly selected and at the same time, the households with children aged 12-24 months represented by each of these MLs were recruited to the study.

To identify the sample for the early childhood home-parenting programme, eight departments were selected located in three geographical regions proximate to Bogotá: Cundinamarca, Boyacá, and Santander (oriental region); Antioquia, Risaralda, and Caldas (coffee zone region); and Huila and Tolima (central region). Within each of these three regions, they identified 32 municipalities (clusters) in which *FeA* had been in operation since its inception in 2002, and where the population ranged from 2,000 to 42,000 inhabitants.[16] The structure mirrored that of the Jamaica study[17] in that it included a psychosocial stimulation component and a micronutrient supplementation component.[18] It was not possible to blind study participants for their allocation to the stimulation treatment. However, testers and interviewers were blind to the treatment status of participants. For a thorough description on the intervention and recruitment process, see Attanasio et al. (2013) and Attanasio et al. (2014).

2.3.2 Sample and attrition

The sample at baseline included 1,420 children in poor households, recipients of the CCT programme *FeA*, from 96 municipalities (clusters). This sample size was computed to detect an effect size of 0.33 of a standard deviation of a Bayley scale on infant development, one of the outcomes of interest in the original study. The sample at follow-up across treatment arms decrease to 1262 children (88% of the children initially recruited).[19] The difference in loss

[16]The municipalities were similar regarding their cultures and customs to design one curriculum—and associated materials such as pictures and books—identifiable to all.

[17]The curriculum of the Jamaica home intervention is currently known as *Reach Up and Learn*. Besides Jamaica, similar structured curricula using home visits has been successfully implemented in Bangladesh, India, Peru, and in another more recent intervention in Colombia. See Grantham-McGregor, Powell, Walker, and Himes (1991) and Gertler et al. (2014), for an overview of the Jamaica study; Grantham-McGregor and Smith (2016) for a review in all countries, and Attanasio et al. (2018) for the FAMI intervention in Colombia.

[18]The Jamaican intervention has documented large impacts on cognitive development and earnings 20 years later (Gardner et al., 2005; Gertler et al., 2014; S. Grantham-McGregor et al., 1991; Walker et al., 2011).

[19]The Bayley scales of infant and toddler development (third edition), were used to assess the early childhood programme impact in cognitive, language, and motor development. More information on the primary outcomes for the original study is included in Attanasio et al. (2014) and in section 2.6. The

(attrition rate) between baseline and follow-up was not statistically significant.[20]

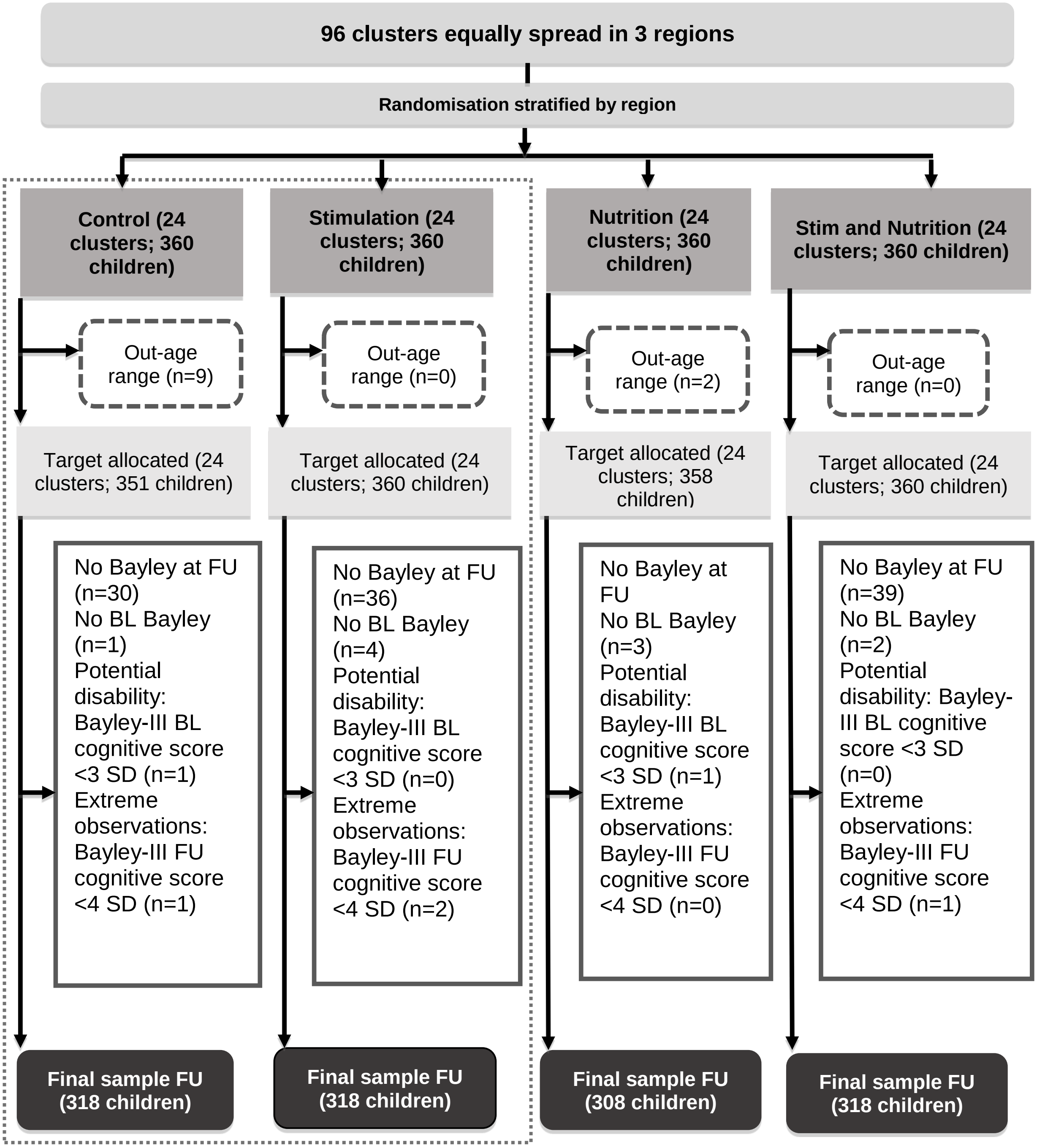
Given the theoretical and empirical motivations explained in Sections 2.1 and 2.2 for my emphasis on the stimulation treatment arm, the main analysis retains the sample from the stimulation arm (i.e. 318 children in 24 clusters) and the sample from the control group (i.e. 318 children in 24 clusters). Hence, the main analytic sample of this paper is for the 636 children who remained in the study at follow-up with complete information on the Bayley scales. The approach to "reduce" the overall sample is similar to subgroup analysis. Though smaller samples have reduced power to detect the overall treatment effect, I avoid the risk of a false-positive result, likely to incur by multiple hypothesis testing given the number of childcare outcomes of interest (four) and the empirical estimation (see sections 2.3.3 and 2.4). The latter does not remove the chance of false-negative result of treatment effect (Brookes et al., 2001). However, as part of the robustness analyses and mirroring Attanasio et al. (2017), I examine childcare outcomes using the study full sample by pooling together all the children that received the stimulation intervention (i.e. stimulation only and stimulation plus nutrition arms, 636 children in 48 clusters) and using as control all the children that were not included in these treatment arms (i.e. nutrition arm and control group, 626 children in 48 clusters).

Reported in Attanasio et al. (2014), Figure 1 below includes a flow of the participants throughout the study of the original design and highlights the main analytic sample (shaded in grey) for the analysis in this chapter.

overall attrition rate of the study across the three treatment arms for children with complete information on the Bayley scales was 10.7%. For the stimulation arm only, the attrition rate was 12.4 % (n=42). From the 42 children, 36 did not have information on the Bayley scales at follow-up, four children did not have information on Bayley scales at baseline, and two extra children who had extreme observations for Bayley scores were excluded from the analysis (see Figure 1).

[20] I conducted baseline checks characteristics for the children who did not have complete information on the Bayley scales at baseline and follow-up, for the stimulation group (n=39) and control group (n=31). No differences were found among groups in predictors and childcare measures.

Figure 1. Flow of children participants through study



*Flow-chart in Attanasio et al. (2014). BL=Baseline, FU=Follow-up. The grey-shaded area corresponds the main analytic sample of this paper.

2.3.3 Outcomes: Childcare measures

As stated before, the primary goal of this chapter is to understand how childcare participation changes for children after parents received the stimulation intervention. The baseline survey included rich data on child development and family characteristics, including a range of questions regarding the child's care arrangement. Parents were asked about the type of childcare used at the time of the survey (current childcare) and the type of childcare children received on a regular basis from Monday to Friday (main childcare), allowing for only one response for current and main childcare options (See Table 1). They were also asked if they had used any source of childcare before baseline collection, i.e. when children were younger than 12-24 months.

To examine the stimulation effect on childcare choices, I construct a categorial variable collapsing the options of childcare included in the questionnaire into four mutually exclusive childcare arrangements, where I matched childcare arrangements responses for current childcare and main childcare. The childcare outcomes include: *public, private, informal* compared against *maternal* care. The selection of childcare categories follows previous early childhood studies looking at the effects of diverse sources of childcare (Blau & Currie, 2006; Bryson, Brewer, Sibieta, & Butt, 2013; Drange & Havnes, 2015; S. Loeb, Bridges, Bassok, Fuler, & Rumberger, 2007).[21]

An important note relates to the fact that examining childcare outcomes was not considered as part of the original study design, neither power calculations were made to detect any effect on childcare measures. Hence the analysis in this chapter complements results of the main findings on child development outcomes in Attanasio et al. (2013, 2014 and 2017); while at the same time, adds new experimental evidence for the childcare literature, where accounting for endogeneity into childcare selection remains the main challenge to overcome (Herbst, 2013; S. Loeb, Fuller, Kagan, & Carrol, 2004; van Huizen & Plantenga, 2015).

Table 1. Childcare outcomes

Childcare outcomes	*Definition (types of childcare)**
Public childcare	If child is in any of the following categories for current and main childcare response: public day care centre, public pre-school or community house/FAMI. This outcome includes institutional types of childcare and licensed homes (e.g. community house/FAMI), all provided/subsidised by the government.
Private childcare	If child is in any of the following categories for current and main childcare response: private day care centre, private pre-school or paid caregiver. This category includes childcare arrangements that families pay a fee for it. It can be institutional or individual caregivers.
Informal childcare	If child is in any of the following categories for current and main childcare response: non-paid. This outcome denotes individual caregivers (such as a family member, friend, neighbour, or other person within or outside the household) that take care of the child without receiving any payment.
Reference category	

[21]Earlier literature has compared various child-care arrangements, including centres, preschools, licensed homes, or individual caregivers, to determine which might hold the most promise for improving cognitive and social-behavioural outcomes (Blau & Currie, 2006; Drange & Havnes, 2015; S. Loeb et al., 2007).

Childcare outcomes	Definition (types of childcare)*
Maternal care	If the child is mainly taken care of by the mother.

*Childcare arrangements included in original questionnaire of the study, matching current childcare and main childcare responses. The reference category in both analyses (I) and (II) is maternal care. The grouping follows previous analyses examining different types of childcare (Blau & Currie, 2006; Drange & Havnes, 2015). In earlier studies looking at "informal childcare", there are some groups generally included in this category: grandparents, other family members and friends or neighbours. However, at its broadest, informal childcare is simply the converse of "formal childcare", then it is defined as "unregulated childcare" (Bryson et al., 2013). For the current analysis, I consider family members, friends, neighbours, or other person within, or outside the household, that does not involve payment (and usually no formal training) as part of the informal childcare category.

2.3.4 Balance at baseline

Table 2 displays summary characteristics of children, their mothers, and their households from the stimulation treatment and control groups (means and standard deviations in parentheses). Overall, estimates indicate characteristics are well balanced between both groups. The age of children in the control group was an average of 18.27 months. Around 29% of children in the control group have received some childcare[22] before baseline collection. Mother's age was 26.12 (6.97) years and only 30% were single; Furthermore about 46% of mothers were classified as depressed (see footnote in Table 2). Only one variable, proportion of households with any grandparent living within the household, is statistically significant and only at the 10% level. Overall, there appears to be excellent balance between the treatment and control groups, as expected due to randomisation.

Table 2. Balance in Baseline Characteristics[23]

Variable	*Control (n=318)*	*Stimulation (n=318)*	*P-value*
Children			
Mean (SD) age in months	18.27 (4.02)	18.05 (3.75)	>0.50
Proportion of Boys	0.50	0.47	0.21
Proportion of children that received any childcare before baseline	0.29	0.20	0.11
Mother			
Mean (SD) age (in years)	26.12 (6.97)	26.87 (6.93)	0.36
Proportion of depressed mothers[1]	0.46	0.39	>0.50
Proportion of single mothers	0.31	0.30	>0.50
Mean (SD) completed years of education	7.52 (3.66)	6.98 (3.59)	0.36
Employed mother	0.48	0.44	>0.50
Household			
Proportion of households with crowding[2]	0.21	0.27	0.39
Mean (SD) household wealth index[3]	0.206 (1.34)	-0.143 (1.98)	0.11

[22]Children who before baseline collection reported to have received any type of formal childcare.
[23]There is an ongoing debate on the RCT literature whether is sensible or not to report p-values when checking for balance between treatment and control groups.

Variable	Control (n=318)	Stimulation (n=318)	P-value
Mean (SD) Number of varieties of play materials[4]	4.29 (1.83)	4.26 (1.79)	0.18
Mean (SD) Number of varieties of play activities[5]	3.69 (1.76)	3.70 (1.72)	>0.50
Proportion of households with any grandparent living within the household	0.34	0.27	0.10

*Main analytic sample. Values presented in percentages unless stated otherwise. [1]Maternal depression was measured using the Spanish translation of the Centre for Epidemiologic Studies short depression scale (CES-D 10). Scores range from 1 to 30; with a score greater than 10 being considered depressed using the reference population norms (O. Attanasio et al., 2014). [2]Binary index that denotes the presence of crowding in the household which takes the value of 1 if household has 3 or more people per room and 0 otherwise. [3]First principal component of household asset and characteristics: dirt floor, solid walls, crowding index, home ownership, sewage, and ownership of car, computer, blender, fridge, washing machine, and cell phone. The index is included in the main findings from Attanasio et al. (2014). Given the household wealth index is constructed using principal component analysis, it might be that the list of items included to construct the index are not depicting an exhaustive picture of the socioeconomic characteristics for the whole study subgroup. Looking individually at other deprivation variables such as proportion of households with crowding, proportion of households with single mothers, we do not detect any differences (nor statistical or in magnitude) among both groups, lessening concerns of unbalanceness. [4]Number of varieties of play materials in the home that the child often played with over the three days before the interview. It includes toys that make or play music; toys or objects meant for stacking, constructing or building; things for drawing, writing, colouring, and painting; toys for moving around; toys to play pretend games; picture books and drawing books for children; and toys for learning shapes and colours. [5]Number of varieties of play activities the child engaged in with an adult over the three days before the interview. It includes reading books or looking at picture books; telling stories to child; singing songs with child; taking child outside home place or going for a walk; playing with child with toys; spending time with child scribbling, drawing, or colouring; and spending time with child naming things or counting.

In Table 3, I examine balance in childcare outcomes between treatment and control groups and estimate the programme effect using differences-in-proportion[24] between treatment and control. All standard errors have been clustered at the municipality level. Results show that at baseline, the proportion of children between treatment and control group for informal childcare are statistically different at conventional values (at the 5% level). In particular, children in treated areas were 4.1 percentage points less likely to be in informal childcare and more likely to be taken care of by the mother. One way to address concerns about imbalance between both groups is to include the variables with observed differences as controls in the empirical estimation. Adding the baseline childcare measures and other baseline predictors will improve statistical power, account for any prior differences (statistically significant or insignificant), and reduce error term (Wooldridge, 2010). The next section discusses the empirical estimation strategy and the list of variables included as part of the impact estimation in childcare choices.

Table 3. Childcare outcomes at baseline and end of intervention (proportions)

Childcare outcomes	Baseline				Follow-up				Change (BL/FU)
	Stim	Control	Diff	p-value	Stim	Control	Diff	p-value	
Public childcare	0.072 (0.031)	0.075 (0.024)	-0.003	>0.5	0.305 (0.046)	0.381 (0.040)	-0.076	0.33	-0.073

[24]Here each childcare measure (dependent variable) is defined as a binary variable.

Childcare outcomes	Baseline				Follow-up				Change (BL/FU)
	Stim	*Control*	*Diff*	*p-value*	*Stim*	*Control*	*Diff*	*p-value*	
Private childcare	0.041 (0.018)	0.050 (0.025)	-0.009	>0.5	0.016 (0.008)	0.035 (0.011)	-0.019	0.35	-0.010
Informal childcare (non-paid)	**0.038*** (0.009)	0.079 (0.015)	**-0.041***	0.03	**0.075*** (0.017)	0.047 (0.010)	**0.028***	0.03	**0.069***
Maternal care	0.846 (0.036)	0.792 (0.034)	0.054	>0.5	0.601 (0.044)	0.535 (0.036)	0.066	0.28	0.012

*p<0.05, **p<0.01, ***p<0.001 for difference with respect to control group. *P-values* for difference in means adjusted for clustering standard errors at municipality level. Standard errors in parentheses.

2.4 Empirical Estimation

A commonly employed strategy for analysis when having categorical dependent variables is Multinomial Logistic Regression. Under this framework, the main estimation model used when the dependent variable consists of mutually exclusive categories where the order is irrelevant (nominal) is the Multinomial Logit Model (MNL). In MNL, the coefficients are interpreted with comparison to a base category, and conditioned to a set of variables, x, that change by unit but not alternative. MNL computes a different continuous latent variable for each choice (i.e. the response probabilities), and these variables are like evaluation scores of each individual. The higher the score for each choice, the more likely that the individual chooses that alternative relative to the baseline (omitted) one (Cameron & Trivedi, 2009; Kropko, 2008; Wooldridge, 2010). Hence, for the choice of childcare, the MNL response probabilities are:

$$P(y_i = j|x_i) = \frac{\exp(x_i\beta_j)}{[1 + \sum_{h=1}^{J} \mathrm{e}\,\mathrm{xp}(x_i\beta_h)]}, \qquad j = 1,2,3$$

$$P(y_i = 0|x_i) = \frac{1}{[1 + \sum_{h=1}^{J} \mathrm{e}\,\mathrm{xp}(x_i\beta_h)]} \qquad (1)$$

where, y denotes the probability of the child i to be enrolled in type of childcare j at follow-up, taking the values of 1 if the child is enrolled in $public$, 2 if the child is enrolled in $private$, 3 if the child is enrolled in $informal$, relative to the base category $maternal$ care, coded with value 0; x_i are case-specific[25] regressors at their baseline values, including: a binary indicator denoting $treatment$ status, set to 1 if child i is in the stimulation group, and 0 if in control group (i.e. the coefficient of this binary indicator is our main parameter of interest, showing whether or not there is an effect of the stimulation treatment); a categorical variable denoting the types

[25]In MNL, coefficients vary but the predictors values are the same no matter which alternative (i.e. childcare choice) is being considered.

of childcare j the child i was at baseline[26], a continuous variable age of child i and its second order polynomial $agesq$ in months, a binary indicator boy for child's sex, a binary indicator $prechildcare$ if child i received any type of childcare before baseline, a continuous variable $momedu$ denoting mother's years of education, a binary indicator $occupation$ denoting mother/main caregiver's working status, a binary indicator $single$ denoting if mother was single or not[27], a binary indicator $grandparent$ denoting if at least one grandparent was living in the household, a continuous variable $wealth$ for household's wealth index[28], and a continuous variable $children6yrs$ denoting the number of children aged six years-old or younger living in the household.[29]

An important consideration is that the error distribution[30] in MNL forces an assumption called the independence of irrelevant alternatives (IIA). This assumption requires that an individual's evaluation of an alternative relative to another alternative should not change if a third (irrelevant) alternative is added or dropped to the analysis (Kropko, 2008). To have consistent and unbiased estimates of the stimulation treatment effect in childcare, I am assuming IIA in Eq (1) holds. Likewise, coefficients in MNL can only be interpreted in terms of relative probabilities. Hence, to obtain conclusions about actual probabilities, we will need to calculate continuous or discrete marginal effects.

Finally, a specific concern for the present analysis is to adjust for imbalance in childcare arrangements, noted in Table 3. I deal with this concern by estimating two models for Eq (1), one only conditioning for baseline childcare (benchmark estimates) to adjust for the small differences detected between treatment and control groups; and a second one conditioning for the rest of the vector baseline characteristics in x_i, as detailed above. The selection of the predictors follows previous childcare analyses.[31] As part of the robustness tests, I estimate Eq(1) using the full sample of the study (i.e. stimulation and stimulation plus nutrition as treatment group versus control and nutrition arm as control group). I also estimate a logit model using a binary indicator of childcare (i.e. collapsing all childcare categories except for maternal care and coded as 1) and comparing against maternal care (coded as 0).

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[26]Categories coded with the same values as in follow-up.
[27]Coded as 1 if the mother reported being single or widowed and 0 if the mother reported being married or in partnership.
[28]First principal component of household asset and characteristics: dirt floor, solid walls, crowding index, home ownership, sewage, and ownership of car, computer, blender, fridge, washing machine, and mobile phone.
[29]The model also includes a dummy variable to account for missing data (28 observations) on mother's characteristics.
[30]In MNL errors are independent and identically distributed according to the type-1 extreme value distribution (i.e. the log Weibull distribution) (Greene, 2012).
[31]For instance, Posadas and Vidal-Fernández (2012) find that grandparents' childcare increases mother labour force participation by around 15 percentage points. Most of the effect is driven by families from socio-economically disadvantaged backgrounds.

2.5 Main results

I start this section by reporting the predicted probabilities for each childcare outcome, including the omitted category, maternal care, for both models of Eq(1): the benchmark model in Columns 1a-4a (i.e. controlling for childcare baseline measures); and the complete model in Columns 1b-4b (i.e. all the controls listed in Section 2.4) in Columns 1b-4b. Looking at the standard deviation estimates in Table 4, we notice that for private childcare, both models predict poorly this outcome. However, there is considerably more variation in predicted probabilities for the rest of the outcomes, specifically for public childcare and maternal care. This might relate that the proportion of children is higher for maternal care, followed by public childcare, regardless of treatment assignment (see Table 3 in Section 2.3.4).

Table 4. Predicted Probabilities

	Public Childcare		*Private Childcare*		*Informal Childcar*		*Maternal Care*	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
Mean	0.345	0.346	0.025	0.023	0.062	0.050	0.568	0.581
Standard Deviation	0.141	0.203	0.017	0.029	0.086	0.066	0.176	0.214

Average Marginal Effects (AMEs) in Table 5 show that the stimulation treatment has no effect on childcare measures except for informal childcare. The stimulation intervention increases *informal childcare*, relative to *maternal* care, by 4.4 to 4.6 percentage points, for the baseline model and the complete model, respectively. The treatment effect is positive and statistically significant (at the 5% level). The sign of the treatment coefficients shows a negative relationship between receiving the stimulation intervention and choosing public and private childcare at follow-up, against maternal care. Yet, none of the effects are statistically significant[32]. We also notice that adding the full vector of covariates do not affect the magnitude of the coefficients (except for public childcare) and slightly improves the precision of the estimates. AMEs and their confidence intervals for both models are plotted in Figure 2.

Table 5. Average Marginal Effects

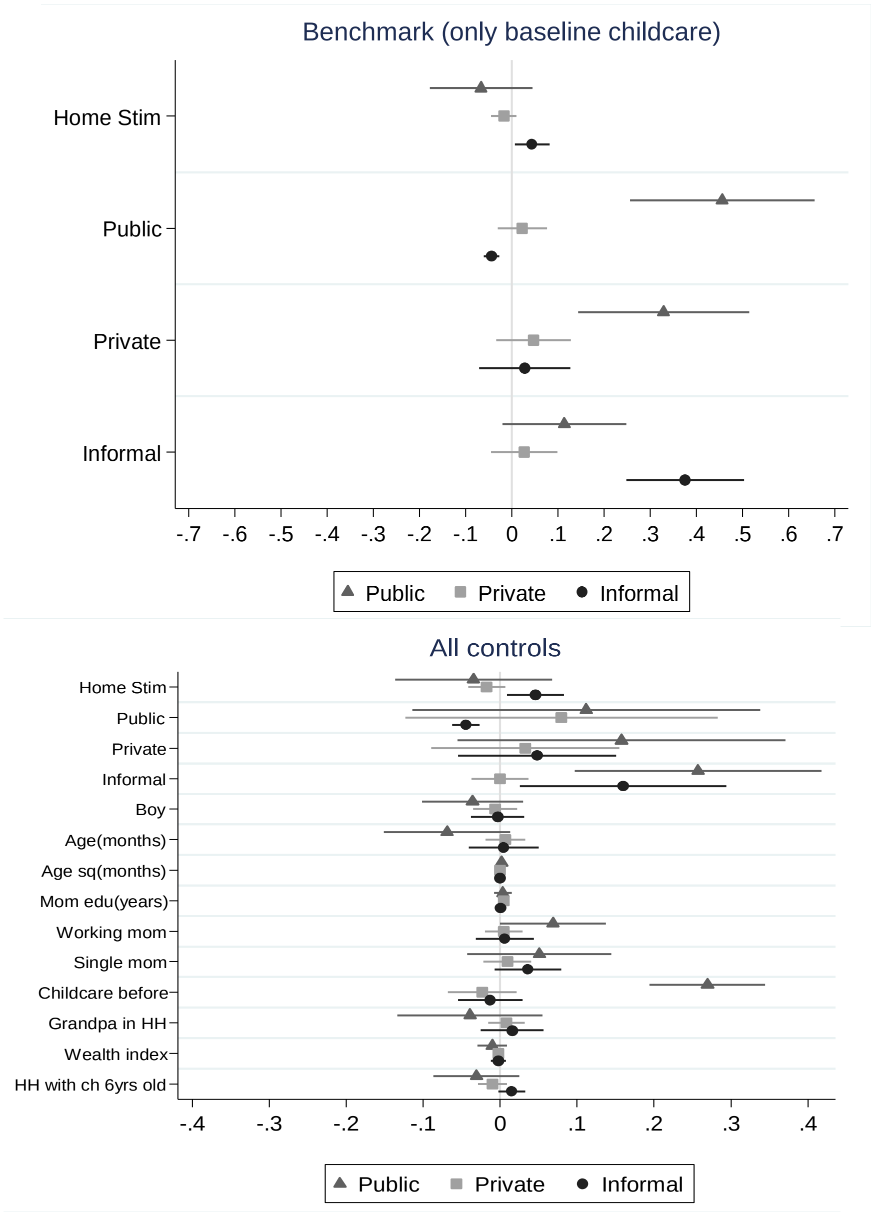
	Public Childcare		*Private Childcare*		*Informal Childcare*	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
Stimulation	-0.067 (0.057)	-0.034 (0.052)	-0.017 (0.014)	-0.017 (0.012)	0.044* (0.019)	0.046* (0.018)
Joint Sig Test	0.075	0.039	0.075	0.039	0.075	0.039

[32]The average marginal effects for the rest of covariates vary depending on the childcare measure. For *public childcare*, pre-baseline childcare and baseline childcare regressors increase *public care* use by 31 to 24 percentage points (*informal childcare* with the largest coefficient). Working mothers increase it by 6.7 percentage points. Regarding *private childcare*, the only significant predictor was mother's years of education, but the influence was less than 1 percentage point. For *informal childcare*, besides the stimulation effect, only baseline *informal childcare* is significant, and augment *informal childcare* use by 18.2 percentage points (see Appendix-Table A1).

	Public Childcare		Private Childcare		Informal Childcare	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
Pseudo R-squared	0.101	0.154	0.101	0.154	0.101	0.154
Observations	632	616	632	616	632	616

*p<0.05, **p<0.01, ***p<0.001 Table shows coefficients for two separate regressions. Standard errors in parentheses are adjusted for clustering at municipality level. Table A1 in the Appendix reports coefficients on the full set of controls.

Figure 2. Average Marginal Effects



*Each figure shows coefficients for two separate regressions.

When fixing all the predictors at their means and estimating Marginal Effects, the magnitude of the probabilities decreases for all outcomes compared to the ones obtained for the Average Marginal Effects in Table 5 above. Being in the stimulation treatment increases less than 2 percentage points the probability of chosing informal childcare rather than from public, private or maternal care (significant at the 5% level). These results are qualitatively similar and complements the main results (Average Marginal Effects). Estimates on Marginal Effects are listed in Table A2 in the Appendix.

For the rest of the variables, Average Marginal Effects and Marginal Effects are similar both in magnitude and statistical significance (see Tables A1 and A2 in the Appendix). In the base model (i.e. when only controlling for the type of childcare at baseline), public, private and informal childcare at baseline show a positive relationship (statistically significant) for public childcare at follow-up relative to maternal care at baseline. For informal childcare at follow-up, baseline public childcare shows a negative relationship with this outcome, while having informal childcare at baseline is associated with 37.6 percentage points more likely of choosing again informal childcare at follow-up. For private childcare, none of the baseline childcare types show any significant relationship. The rest of the covariates in the complete model seem to have only a predictive association for public childcare use at follow-up. Mother working at baseline is linked with an increase of 6.9 percentage points in the probability of using public childcare at follow-up relative to maternal care; the predicted probability is higher if the child received any type of childcare before baseline data collection, where the increase can be up to 27 percentage points of choosing public childcare relative to maternal care at follow-up. The increase in the number of children aged six years old or younger living in the household only leads to a marginal increase of 1.5 percentage points in the use of informal childcare at follow-up. As mentioned before, accounting for the full list of predictors does not affect in magnitude or significance the stimulation treatment effect in childcare choices, confirming the balance in randomisation conditions.

2.5.1 Robustness checks

In this section, I probe the main results further but now using the complete sample of the study for the children who remained at follow-up, grouping both stimulation treatment arms (i.e. treatment group) and the nutrition arm and control group (i.e. control group) as in Attanasio et al. (2017). I find there is no impact of the stimulation treatment on any of the childcare choices after the intervention. Average Marginal Effects in Table 6 suggest that the stimulation intervention decreases public and private childcare, and also that increases informal childcare use relative to maternal care, as in main results in Table 5, but none of these effects are statistically significant at conventional levels (see also Figure A4 in the Appendix). Although the effect of the treatment disappears for informal childcare, it does not come as a surprise, as the findings in Attanasio et al. (2014) document no significant interaction of the stimulation with nutrition and no impact in child's cognitive development for the nutrition arm.

Table 6. Average Marginal Effects

	Public Childcare		*Private Childcare*		*Informal Childcare*	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
Stimulation	-0.025 (0.037)	-0.008 (0.035)	-0.007 (0.009)	-0.006 (0.008)	0.020 (0.014)	0.021 (0.014)
Joint Sig Test	0.489	0.458	0.489	0.458	0.489	0.458
Pseudo R-squared	0.085	0.123	0.085	0.123	0.085	0.123
Observations	1,258	1,230	1,258	1,230	1,258	1,230

*p<0.05, **p<0.01, ***p<0.001 Table shows coefficients for two separate regressions. Standard errors in parentheses are adjusted for clustering at municipality level. Table A3 in the Appendix reports coefficients on the full set of controls.

A potential concern might be that there are not enough children for each of the childcare categories of interest compared to the large sample of children using maternal care, regardless of treatment status. As part of the robustness checks, I proceed and inspect the treatment effect for the binary indicator of childcare (i.e. collapsing all childcare categories in one) relative to maternal care. We notice there is a negative relationship between the stimulation intervention and the probability of using any childcare at follow-up, relative to maternal care, although the effect is not statistically significant. The caveat when using the logit model, particularly collapsing all the childcare information into one category, can result in loss of information and statistical power. The results for the logit model appear to be driven by the children allocated in public childcare, as results are similar to the ones obtained in this category when using MLN. The Average Marginal Effects for the rest of the coefficients are reported in Table A5 in the Appendix

Table 7. Average Marginal Effects

	Any Childcare	
	(1a)	(1b)
Stimulation (AME)	-0.049 (0.051)	-0.017 (0.049)
Joint Sig Test	0.342	0.724
Pseudo R-squared	0.088	0.127
Observations	636	620

*p<0.05, **p<0.01, ***p<0.001 Each column is a separate regression. Standard errors in parentheses are adjusted for clustering at municipality level.

2.6 Further Evidence

In this section I present results for two extended models for Eq(1) including the Bayley score as control to examine if the stimulation treatment effect is sensitive to “adjustments” by the “observed” child skills.

An important assumption in the literature explaining parental investments differentials is that parents adjust their behaviour and investments according to the skills they observe in their children. It might be the case that the null impacts on public and private childcare choices are due to omitted inputs in the estimation (e.g. a cognitive measure of the child). As discussed earlier, one reason to focus on the stimulation treatment is the positive effect on child cognition and language development measured following the end of the intervention (O. Attanasio et al., 2017; O. Attanasio et al., 2014).[33] I proceed to investigate childcare decisions for two extended models controlling for the aggregate index of the child's cognitive outcome (observed at baseline). The index aggregates all the subscales from Bayley-III obtained to assess the impact of the intervention in child development. The aggregate Bayley-III Index includes five subscales measuring: cognition, receptive language, expressive language, fine motor, and gross motor.[34] Inter-rater reliability (Cronbach's alpha) was above 0.9 on each subscale at baseline and above 0.8 at follow-up (See Table A6 in the Appendix). I transform the aggregate index into a *z-score* with mean 0 and standard deviation 1. Average Marginal Effects in Table 8 are consistent with the findings obtain in the main results section. Relative to maternal care, the stimulation decreases, on average, the probability of choosing public and private childcare, while increasing the probability of informal childcare (significant at less than 5% level). The Bayley Index shows a negative association with public childcare at follow-up and positive for private and informal childcare, but all coefficients are small in magnitude and none of them are statistically significant. We confirm the magnitude of the stimulation treatment effect is unaffected when controlling by the Bayley's cognitive index.

Table 8. Average Marginal Effects: Bayley Index

	Public Childcare (1a)	*Private Childcare* (2a)	*Informal Childcare* (3a)
Stimulation	-0.033	-0.017	0.046*
	(0.052)	(0.012)	(0.019)
Bayley Index	-0.028	0.012	0.001
	(0.041)	(0.014)	(0.017)
Joint Sig Test	0.052	0.052	0.052
Pseudo R-squared	0.155	0.155	0.155
Observations	616	616	616

*p<0.05, **p<0.01, ***p<0.001 Table shows coefficients for two separate regressions. Standard errors in parentheses are adjusted for clustering at municipality level.

[33]Cognition improved by 26% of a standard deviation (SD) (p-value 0.002) and receptive language by 22% of a SD (p-value 0.032) (Attanasio et al., 2014).
[34]For more information on the Bayley outcomes related to the intervention see Attanasio et al. (2014) and Attanasio et al. (2017). For general information on the Bayley scales see Bayley (2006).

2.7 Suggestive evidence of mechanisms

The main results in Table 5 indicate the stimulation treatment effect on informal childcare is robust to controls for different characteristics, including a child's development score. They also show that for the rest of the childcare outcomes, the intervention has zero effects. While the experimental design of this evaluation does not allow disentangling the importance of the various mechanisms, we observe there is generally a high persistence to remain in the same type of childcare the child received at baseline, even after parents obtained information and training on the importance of quality interactions at this life period. This section explores treatment effects in two additional aspects, one previously investigated in Attanasio et al. (2017) and the other relates to mother's labour market outcomes.

2.7.1 Time use: play time

Although we do not observe any shifts in maternal care following the stimulation intervention, we look into whether the quality of care at home has improved. In Attanasio et al. (2017), authors unpacked that one channel through the stimulation treatment led to higher cognitive development for treated children was an increase in the parental material and time investments. In the study survey, they collected information on various stimulation activities conducted at home and reported by the mother/main caregiver using the UNICEF Family Care Indicators (FCI) (Frongillo, Sywulka, & Kariger, 2003). This instrument includes questions about the types and numbers of play materials around the home and about the types and frequencies of play activities the child engages in with an adult. To measure play activities, they employ questions about the activities performed by the primary caregiver or any other adult older than 15 with the child in the last 3 days. I investigate if the stimulation intervention affects three time-investment outcomes with a focus on play time, as follows:

1) Total number of play activities, using alternative time use raw measures than the ones employed in Attanasio et al. (2017), also collected in the survey;
2) A factor index[35] derived from a set of play time binary items and transformed into a *z-score*;
3) Total number of hours the main caregiver spent in play time activities in the last working day[36];

[35]Using maximum-likelihood factor method estimation and retaining one factor. Results of the factor analysis, i.e. factor loadings and the amount of variance explained, are reported in Table A8 in the Appendix.

[36]The questions about play time referred to the amount of time spent *yesterday* doing that specific activity with the child. If *yesterday* was a holiday or weekend day, then they were asked to remember about the last working day (from Monday to Friday).

I examine the impact of the stimulation intervention on these three play time outcomes, but also how these outcomes relate to the types of childcare observed at baseline in an OLS regression model. Interest in play time stems from its link with physical activity and child development in very young children (e.g. aged 0 to 5). Physical activity (play time) in early childhood has been associated with improvements in gross motor and fine motor skill development, and reduced levels of chronic stress (Stegelin, 2005). As children younger than 5 years-old spend the majority of their time at home or in day care settings, parents and day care providers have a great influence on their play time. Hence, play time and physical activity are closely link to child development measures as the Bayley scales. Understanding how play time relates to childcare, and how early childhood interventions could improve overall play time, is important as part of the dynamics in the child's development process and, as one channel that the stimulation treatment lead to improvements in child development. One reason of the scant evidence documenting the relationship between play time and parental care, is due to the lack of data outside of the day care or preschool setting (Carsley et al., 2017). Although we do not observe any changes in maternal care as a result of the stimulation treatment, we examine if the intervention led to an increase in the levels of playtime at home as a proxy of growth in the quality of the home environment. Looking at this relationship also provides useful information documenting the relationship between playtime and maternal care, overcoming the data limitation in earlier studies.

Table 9 lists the binary items (raw measures) and proportion of children in the stimulation and control groups engaged in each activity at both baseline and follow-up. We observe that in some activities (items 3-7) the proportion of children in control group is higher at baseline that children in the stimulation group but differences are not statistically significant. The relationship shifts at follow-up, were now the proportion of children engaged in play activities is higher than in the control group, but only statistically significant (at the 5% level) for raw measure (5) (i.e. caregiver telling stories alone with the child).[37]

Table 9. Proportion of children engaged in activities with main caregiver

	Baseline			**Follow-up**		
	Stim (1)	*Control* (2)	*Mean Diff* (3)	*Stim* (4)	*Control* (5)	*Mean Diff* (6)
1. Caregiver play alone with child and her/his toys	0.604	0.569	0.035	0.438	0.434	0.003
2. Caregiver play with child & other kids	0.247	0.243	0.003	0.208	0.181	0.028
3. Caregiver dance/draw alone with child	0.378	0.434	-0.056	0.288	0.250	0.038
4. Caregiver dance/draw with child & other kids	0.122	0.142	-0.021	0.160	0.122	0.038
5. Caregiver read/tell stories alone to child	0.087	0.104	-0.017	0.181	0.118	0.063*

[37]Item (6), caregiver telling stories to the child and other kids was significant only at the 10% level.

		Baseline			Follow-up		
		Stim (1)	*Control* (2)	*Mean Diff* (3)	*Stim* (4)	*Control* (5)	*Mean Diff* (6)
6.	Caregiver read/tell stories to child & other kids	0.028	0.038	-0.010	0.076	0.042	0.035
7.	Caregiver play outside with child	0.344	0.347	-0.003	0.274	0.257	0.017
Observations		576			576		

*p<0.05, **p<0.01, ***p<0.001 Table reports difference in means between treatment and control groups. One item not reported in table and excluded as part of the play time analysis, was if caregiver spent time bathing/dressing/feeding the child, with caregivers reporting doing this activity by more than 98% at baseline and 97% at follow-up for both groups.

Before examining the impact of the stimulation treatment with play time and the relationship with childcare at baseline, is sensible to first investigate if our childcare variables and the outcomes of play time correlate or not. Table 10 displays the correlation matrix between the types of care and the play time outcomes at baseline for the main analytic sample (n = 636). These preliminary estimates confirm that as expected, there is a negative association between any type of care, different from maternal, with each of the play time outcomes of interest. Maternal care at baseline is positively associated with a 0.166 increase in the number of play activities and a 0.179 increase in hours spent in play activities (both significant at the 5% level).

Table 10. Correlation matrix of play time and childcare at baseline

	Play time outcomes			*Types of care*			
	Number of play act	Play Factor Index	Hrs in play activities	Public Childcare	Private Childcare	Informal Childcare	Maternal care
Number of play activities	1.000						
Play Factor Index	0.921*	1.000					
Hrs in play activities	0.719*	0.633*	1.000				
Public Childcare	-0.091*	-0.091*	-0.078*	1.000			
Private Childcare	-0.033	-0.016	-0.095*	-0.062	1.000		
Informal Childcare	-0.149*	-0.016	-0.121*	-0.070	-0.054	1.000	
Maternal care	0.166*	0.078	0.179*	-0.601*	-0.465*	-0.529*	1.000

*p<0.05, **p<0.01, ***p<0.001

Table 11 presents estimates of the impact of the stimulation treatment in the play time outcomes and the coefficients on the types of care at baseline. I found some evidence that children in the stimulation group exhibit an increase of 0.26 activities in the number of play activities, a 0.11 standard deviation increase in the play time factor index, and 0.031 hours more of play in any regular day, but unlike Attanasio et al. (2017), none of these impacts are statistically significant. Several reasons relate to the difference in these results including using different time use measures to identify effects, measurement error in the time use outcomes, and using different treatment and control groups comparisons.[38] Regarding baseline childcare,

[38]In Attanasio et al. (2017), authors estimate the impact of the stimulation treatment by pooling the two groups that received it (stimulation and stimulation + nutrition groups) against the other groups that did not (only nutrition and control groups). I conduct as robustness test the same two group comparison in

there are expected negative relationships (large in magnitude and statistically significant) between all play time outcomes and the baseline childcare categories relative from maternal care. The negative associations are stronger and larger in magnitude if being in private childcare at baseline in contrast of being in maternal care.

When pooling together both treatment groups (i.e. stimulation and stimulation plus nutrition groups) and both "control" groups (i.e. control and only nutrition groups), the stimulation treatment has a positive significant impact in the number of play activities, increasing them by 0.36 activities more for children allocated in the intervention groups (significant at the 1% level). Estimates are listed in Table A10 in the Appendix.

Table 11. OLS: play time

	Play activities	*Factor Index*	*Hrs of play*
	(1)	(2)	(3)
Stimulation treatment	0.257	0.106	0.031
	(0.197)	(0.168)	(0.197)
Public childcare at BL	-0.206	-0.085	-0.100
	(0.290)	(0.200)	(0.304)
Private childcare at BL	-0.774***	-0.569**	-0.777***
	(0.223)	(0.215)	(0.215)
Informal childcare at BL	-0.043	-0.275	-0.006
	(0.350)	(0.266)	(0.348)
Baseline outcome (number play activities, factor index, total hours of play)	0.207**	0.127*	0.109**
	(0.040)	(0.052)	(0.036)
Joint Sig Test (=0)	0.20	0.53	0.88
R-squared	0.101	0.100	0.077
Observations	574	574	574

*p<0.05, **p<0.01, ***p<0.001. Each column is a separate regression. Standard errors in parentheses are adjusted for clustering at municipality level.

2.7.2 Mother characteristics

In this section we look at the stimulation treatment effect on labour maternal supply to see if they are consistent with the childcare estimates. In the traditional female labour supply model, formal childcare is assumed to be provided by the market and considered a perfect substitute of maternal care. However, in countries where childcare services are scarce, and/or prices of private childcare are very high, families tend to rely on informal childcare provided by relatives (Arpino et al., 2012). I examine if the intervention has any effect on mother's working status, conditioning for mother's working status at baseline, an indicator of mother's depression status, and the type of childcare used before the intervention. Exploiting the rich information from the household survey, information on mother's working status and maternal depression was collected at baseline and follow-up. Both employment and depression status

Table A7 in the Appendix. Results remain the same for outcomes in Columns (2) and (3), while outcome on Column (1) exhibits a positive significant increase. See Table A10 in the Appendix.

are included in the model as binary indicators. In this specification, the stimulation treatment has no effect on any of the mother's labour market outcomes. As expected, mother's working status at baseline is the strongest predictor of mother's employment status at follow-up. If the mother is employed, it leads to 35 percentage points more likely of also being working at follow-up. Consistent with earlier studies on the role of childcare to facilitate mother's participation in the labour market, being in any type of childcare, relative to maternal care is associated with an increase between 16 and 20 percentage points more likely in the probability of working at follow-up. Estimates on this exercise are consistent with the childcare findings in Table 5.

Table 12. LPM estimates: Mother characteristics

	Mother is employed	*Mother is employed (extended)*
	(1)	(2)
Stimulation treatment	-0.009	-0.010
	(0.040)	(0.041)
Public childcare at BL	0.204***	0.203***
	(0.070)	(0.071)
Private childcare at BL	0.159*	0.159*
	(0.091)	(0.092)
Informal childcare at BL	0.201**	0.201**
	(0.078)	(0.078)
Mother is depressed		-0.004
		(0.036)
Mother is employed at BL	0.346***	0.346***
	(0.037)	(0.037)
R-squared	0.102	0.100
Observations	595	595

*p<0.05, **p<0.01, ***p<0.001 Each column represents a separate regression omitting the constant. Standard errors in parentheses are adjusted for clustering at municipality level. Maternal depression was measured using the Spanish translation of the Center for Epidiemiologic Studies short depression scale (CES-D 10). Scores range from 1 to 30 and a score greater than 10 is considered as depressed using the reference population norms (Attanasio et al., 2014)

2.8 Discussion and Conclusion

The present analysis offers experimental evidence of how a stimulation intervention, might also influence childcare decisions besides promoting development. I exploit a randomised study design of an early childhood intervention to examine the impact on different types of childcare relative to maternal care under a Multinomial Logit framework. The evidence shows that the stimulation intervention has a positive impact on the increase of informal childcare (4.6 percentage points) and no impact for the rest of childcare outcomes. The stimulation treatment effect is robust to the inclusion of different covariates, including a child's development score.

Several explanations might help to understand the null results of the stimulation treatment for the rest of the childcare outcomes. The first relates to the intervention's original design, which was not conceived to detect any effect on childcare outcomes. Another might relate to the relatively short exposure to the intervention, only lasting 18 months and failing to provide with comprehensive information on various redistributions of parental investments they could implement. This also relates to the first reason, as 18 months were conceived to have an impact on child development, measured through the Bayley scales, nor on informing about the potential advantages (disadvantages) on the choice of care. A third reason involves the small percentage of children distributed among the different types of childcare examined, in contrast with the large proportion of children being taken care of by their mothers, regardless of treatment allocation.

On the positive impact on informal childcare participation, this result reflects the second part of the two potential hypothesised relations between the psychosocial stimulation and the choice of childcare, in this case informal childcare. Parents might have perceived the stimulation treatment increased the child's skills and would not benefit from being in a more formal childcare setting. This is consistent with the complementarity feature central to the dynamic model of skill formation (Cunha & Heckman, 2008). Second, the stimulation intervention delivered information to the parents about their child's skills, increasing parental confidence and their knowledge in child nurture, hence supplementing the need for formal childcare and using informal care arrangements instead to save costs. In this scenario, the stimulation treatment might be acting simultaneously as a substitute for childcare and complement of parents' knowledge. Likewise, the result might be hinting parental preferences for "internal" childcare arrangements. Mothers may be less willing to entrust their children to institutions and may prefer either to care of their children themselves or to have them in the custody of relatives, especially when they are very young (Arpino et al., 2012). No significant association was found related to the age of the child predictor, somewhat similar to previous early childhood findings looking at the starting age of childcare, with inconclusive results. Moreover, many parents might use a combination of informal and formal childcare (including early years education) and, so, a rise in the use in one will not necessarily lead to a fall in use of the other (Bryson et al., 2013). In the interest to avoid this misinterpretation scenario, I delimit the analysis to mutually exclusive childcare arrangements.

There are several caveats to the present analysis. One limitation relies on focusing the analysis on the stimulation treatment arm only. This has direct implications for the external validity of the conclusions, although some concerns on this regard are overcome by the different robustness tests conducted. Furthermore, despite the stimulation treatment affected informal childcare participation, and previously improved cognitive and language outcomes (O. Attanasio et al., 2017; O. Attanasio et al., 2014), is not enough evidence to establish the causal impact of childcare in other child's outcomes. However, the results hint to the possibility of using a randomised early childhood intervention as an instrument to explore the causal impact of informal childcare in later life outcomes from the child or longer-term effects in maternal labour participation. The results also indicate that the effectiveness of scaled interventions using pre-existing conditions and infrastructure might be a promising approach to extend potential benefits and promote future investments in human capital.

Overall, more studies on how early childhood programmes complement rather than substitute for family care are needed. Previous early childhood literature shows that successful interventions alter parental behaviour. Understanding why this happens, how good parenting practices can be promoted, and through which channels parenting influences child development are crucial tasks for upcoming studies (Heckman, 2014; Heckman & Mosso, 2014). Likewise, it is essential to have a more comprehensive understanding of informal childcare services, particularly for the disadvantaged population. This type of care should be included in the discussion of public childcare, as it is usually overlooked because it has been seen purely as a “family matter,” and hence not of interest to public policy (Bryson et al., 2013). Still, earlier findings have shown that the use of informal childcare, particularly grandparents, significantly increases mothers’ labour participation, with stronger effects in disadvantaged families (Arpino et al., 2012; Posadas & Vidal-Fernández, 2012). Future analyses should focus on identifying profiles and characteristics of informal childcare providers to understand potential mechanisms that drive this impact and enhance the effectiveness of early childhood interventions in outcomes of interest. Learning about the interactions among childcare providers and informal childcare is necessary for policies aiming to improve early childhood and subsidise childcare services for low-income populations.

Lastly, resources to support childcare decision-making should acknowledge the multiple interconnected factors that shape how decisions are made within the household and the fact that preferences for different features of child care arrangements may vary by the characteristics of the families (Forry, Tout, Rothenberg, Sandstrom, & Vesely, 2013; Weber, 2011).

Chapter 3 The relationship of time-inputs on skills acquisition in Peru: a longitudinal analysis

3.1 Introduction

Skills give people the tools to shape their lives, to create new skills and to flourish (Kautz et al., 2014). Questions like how to foster basic skills, when is the optimal time to invest in them (to yield the highest returns), what's the role of each actor into the skill development process, among others, have increasingly caught the attention of researchers and education practitioners alike. The term skill is entangled to the concept of human capital. According to Cunha and Heckman (2008), fostering and accumulation of human capital is a dynamic and symbiotic process developed throughout the life-cycle. In short, we develop different skills through each life stage. These skills are the product of a variety of investments and inputs at each period, which in turn complement the future investments and stocks of distinct types of skills. They claim that each life stage might represent a critical or sensitive period in the formation of skills. Sensitive periods are those periods where investment is especially productive; critical periods are those periods when investment is essential. Critical and sensitive periods differ across skills and investments should target those periods (Cunha et al., 2010; Heckman & Mosso, 2014; Kautz et al., 2014).

The analysis on this chapter relates to the growing literature documenting the process of skill acquisition and complements recent studies trying to assess the causal effect of child work on child's skill development within developing and mid-developing economies (Emerson, Ponczek, & Souza, 2017; Keane et al., 2018). One first goal is to understand the role of children's time use to produce a vocabulary score (i.e. the Peabody Picture, and Vocabulary Test (PPVT)), considering this outcome as proxy for cognitive skill[39], and two psychosocial measures, the Self-Esteem and Self-Efficacy indexes, used as proxies for psychosocial skills[40]. I focus the analysis of the skill formation process during three important and less documented life-stages in the child's development cycle, childhood (ages 6-9), early adolescence (ages 10-14) and transition to adolescence (age 15). I argue that child's time use might be an important input or determinant for skill production, in the same fashion as other empirically confirmed factors such as parental education or maternal time (P. Carneiro & Rodriguez, 2009; Del Bono, Francesconi, Kelly, & Sacker, 2016; Ermisch, Jäntti, & Smeeding, 2012; Molnár, 2018), particularly throughout the age-periods mentioned above. My interest is

[39] See section 3.3.1 for a discussion on selecting this outcome as proxy for cognitive skill.
[40] See section 3.3.1 for a discussion on selecting both outcomes as proxies for psychosocial skills.

to detect, among the range of activities in the 24 hour-day of the child, which one is more productive (if any) to produce the two skills (i.e. three outcomes) of interest.

The second goal of this chapter is to investigate the trade-offs of child work among each alternative time input activity. Linked to time distribution, most of the research for developing countries investigate the causes and consequences of child work with emphasis on its link with schooling (e.g. attendance), rather than learning (Bourguignon, Ferreira, & Leite, 2003; Dumas, 2012; Emerson et al., 2017; Ravallion & Wodon, 2000).

As possible input or determinant for skill production, time allocation has received less attention, in contrast with family income, parental education, quality of home environment and school's inputs, childcare and early childhood programmes, and others (Garcia, Heckman, Leaf, & Prados, 2016; Heckman et al., 2013; P. Todd & Wolpin, 2007). There are few empirical papers that study the role of time use on skill acquisition of children (P. Carneiro & Ginja, 2016; D. Del Boca, Flinn, & Wiswall, 2016; Del Bono et al., 2016; Fiorini & Keane, 2014; Hsin & Felfe, 2014; Nicoletti et al., 2017). They have primarily focused on parental time, rather than the child's own time, and in developed countries settings. Likewise, most of the studies investigating the impact of child work, have only included market work as part of their definition of child labour. I consider a broader definition of child work, including the production and domestic work within the children's homes, a common situation in developing countries (Morrow & Boyden, 2018).

Given the two research objectives and previous findings on the literature, I hypothesise that according to the type of activity the child spent the most, it will in turn influence (positively or negatively) the production of cognitive or psychosocial skills. Time-inputs in educational activities might be more productive (positive) for the PPVT score (cognitive skill), while time-inputs in leisure and child work might have more influence for the Self-Esteem and Self-Efficacy indexes (psychosocial skills). An expected positive relationship in the case of leisure inputs and negative in the case of child work. To test these relationships empirically, I estimate linear production functions of child cognitive and psychosocial skills following a dynamic human capital accumulation approach (Cunha & Heckman, 2008). Under this framework, I combine current and past time inputs and other factors to examine the relevance of earlier time inputs relative to later time inputs to produce three different "skills": the PPVT, the Self-Efficacy, and Self-Esteem indexes for Peru, a country with both high levels of inequality and rates of child work. I take advantage of rich time use measures collected from the child by Young Lives, an ongoing longitudinal study on childhood poverty. A major challenge when measuring skill production is dealing with endogeneity on inputs (e.g. adjusting time investments according to the realisation of previous outcomes), which may bias the estimate. I tackle endogeneity issues on time inputs by estimating a wide range of models, including standard OLS, cumulative, cumulative value-added, cumulative value-added-instrumental variables, and within-child fixed effects. All or some of these empirical strategies are applied in Borga (2018), Keane et al. (2018), Del Bono et al. (2016), Fiorini and Keane (2014), and Todd and Wolpin (2007). The works of Borga (2018) and Keane et al. (2018) are the closest related contributions. Both studies estimate skill production functions using Young Lives data and children's own time but excluding the last round of survey data. Furthermore, Keane et al. (2018) focus on the impact of child work in two cognitive outcomes, while Borga (2018) excludes Peru from the analysis.[41]

Results indicate that, overall, time inputs effects are marginal for both types of skills, but we document important differences in the type of activities influencing each outcome by age, confirming that the production functions for each skill are indeed different (Cunha & Heckman, 2008; Del Bono et al., 2016). We do find significant measurement error concerns in the Self-Efficacy Index which made us exclude the estimates and focusing on discussing results on the verbal score and the Self-Esteem index. There are some key findings to summarise. First, daily time in educational activities, such as the time spent studying and at school during the school-age period and when transitioning into adolescence is crucial for verbal development, leading to an increase of up to 0.077 s.d. The same results indicate that an extra hour spent studying per day is slightly more productive than extra daily hours spent at school for the verbal score. Second, for the Self-Esteem Index, current time (at age 15) spent in leisure and past (at age 8) and current time spent in child work is detrimental for this skill at age 15, decreasing this outcome between 0.057 and 0.063 s.d, respectively. Third, on the trade-off analysis of child work, I only find small detrimental effects of current time spent in paid work (at age 15), particularly when it crowds-out time spent in educational activities for the PPVT score and no effects for the Self-Esteem Index. Fourth, outcome persistence (i.e. the effect of the lagged outcome) is strong for the PPVT score, accounting at least for 50% of current PPVT score (0.499 s.d.), and significantly less for the Self-Esteem index, only about 17% (0.168 s.d.). Fifth, the consistent detrimental effect of current time (age 15) spent in leisure is robust across different empirical strategies, when estimating alternative specifications to account for missing inputs, and when analysing the trade-off and contribution of each time input activity into each skill. Unfortunately, we are not able to disentangle which are the specific leisure activities driving the negative result, as opposed when we examined the trade-offs in child work. As discussed in Keane et al. (2018), the answer to the question whether child work is negative for skill development is dependent upon the alternative time inputs investments and which type of

[41]Other studies using Young Lives data and estimating production functions focusing on other outcomes include Attanasio, Meghir and Nix (2015) estimating joint functions for production of cognition and health using non-linear models and latent constructs of parental investments and past parental health; and Sanchez (2017), who estimates separate functions for cognitive and non-cognitive skills using early nutrition (i.e. height-for-age) as main input and structural models for estimation.

work is considered. For Peru, paid work at age 15 is the only child work activity with detrimental effects in the verbal score.

Altogether, the findings in this chapter contribute to the literature by 1) confirming the evidence with respect to the importance of time investments in education for cognitive skills and differences in malleability among each type of skills; 2) reveals key insights for the process of skill development for one psychosocial skill; 3) adds on to the limited literature documenting any outcome linked to leisure activities for aged-school children; 4) expands on the current studies using Young Lives data by including the latest survey round of data collection; and 5) have important implications in terms of data collection and policy design. There is still much scope to improve validation, collection, and measurement of psychosocial skills. This is crucial if we aim to document the causal processes and mechanisms for skill formation in these types of skills, and for the design of developmentally timed interventions to foster these skills. Likewise, policies aiming to increase human capital linked to time distribution should focus on allowing children to increase their time spent in school or studying (e.g. extended school-days) rather than focusing on reducing domestic child work. Policies aiming to remove children from the labour market should also aim to crowd-in time spent in educational activities, rather than just “freeing-up” child work time.

The chapter proceeds as follows. Section 3.2 expands on the related literature findings. Section 3.3 describes the data, outcomes, and sample characteristics. Section 3.4 presents the empirical strategies employed. Main results are discussed in Section 3.5, and further evidence is presented in Section 3.6. Finally, Section 3.7 concludes.

3.2 Related Literature

On the human capital literature, there is extensive evidence, that early childhood (from 0 to 5 years) is a sensitive period for child development and investments[42] made at this stage lead to higher rate of returns and positive long-term effects (O. Attanasio, 2015; Cunha, 2014; Heckman et al., 2013; Reynolds & Temple, 2008). The same literature documents that gaps in skills between individuals and across socioeconomic groups emerge at early ages and appear to be strongly linked to inequality of human capital investments (O. Attanasio, 2015; Cunha, 2014). Not until very recent, there has been a grow in studies documenting adolescence as another sensitive period for investment, particular in what concerns to

[42]The most successful investments relate to high quality early childhood programmes, targeting socioeconomic disadvantaged families and children. Successful early childhood interventions scaffold children and supplement parenting. They generate positive and sustained parent-child interactions that last after the interventions end (Heckman & Mosso, 2014).

development or malleability[43] of psychosocial skills (Duckworth, Almlund, & Kautz, 2011; Goodman, Joshi, Nasim, & Tyler, 2015; Heckman & Mosso, 2014; Kautz et al., 2014). Steinberg (2014, 2008) highlights adolescence as a development process that needs to be nurtured, and where it is possible to minimise risky behaviours by building up on resiliency factors. Adolescents are very responsive to rewards and to reward-seeking behaviour and show reduced responsiveness to adverse stimuli such as punishment (Spear, 2013).

On time use, most of the empirical evidence has examined the time parents spend interacting with children, rather than how children themselves spend their time (Borga, 2018). A consistent finding in these studies is that maternal time is an important determinant of skill formation for children. Del Bono et al. (2016) estimate the relationship between maternal time inputs and early child development for UK children. They find the more time mothers spend with their children the higher cognitive and non-cognitive outcomes over ages 3–7. The magnitude of the effect is quantitatively large and corresponds to 20–40% of the magnitude of the effect of having a mother with a university degree as opposed to having a mother with no qualification. Carneiro and Ginja (2016) use parental time and other inputs to measure the response of parental investments in children in time and goods to permanent and transitory income shocks. Carneiro and Rodriguez (2009) find that more time with mothers leads children (particularly those aged three to six years) to perform better in cognitive tests. Fiorini and Keane (2014) analyse how Australian children aged between 1-9 years old allocate their time into several different activities (not just time with parents). They find that time spent in educational activities, mainly with parents, is the most productive input for cognitive skills, while non-cognitive skills are uncorrelated to different types of time allocations (Del Bono et al., 2016). On the productivity of parental investments by age, Corneus, Laucht and Reuss (2012) show that that parental investments are most efficient for both types of skills directly after birth and less efficient at age eight (sensitive period). After age eight, they even become ineffective (critical period).

Few empirical exceptions documenting results on children's own time include Del Boca et al. (2014) and Caetano, Kinsler and Teng (2017), both using data from the Child Development Supplement of the Panel Study of Income Dynamics (PSID); and Borga (2018) and Keane et al. (2018), using Young Lives data. In their study, Del Boca et al. (2014) estimate adolescents production functions of cognitive skills. Their results point that child's own time investment is more influential than mother's time investment during adolescence, but maternal time inputs are more important when children are 6–10 years old. Caetano, Kinsler, and Teng (2017) examine how time allocation affects children's skills accumulation by applying a test of

[43]Malleability (grade of plasticity) is set to describe the skill flexibility to change, adapt or improve through intervention or investments.

exogeneity[44] to search for valid specifications. Their results indicate that active time with adult family members, such as parents and grandparents, is the most productive for cognitive skill formation. Borga (2018) estimates production functions for cognitive and psycho-social skills for three of four countries in the *Young Lives* study, Ethiopia, Vietnam, and India; and for the two cohorts of children, an Older Cohort, born in 1994-1995, and a Younger Cohort, born in 2001-2002. He finds that child involvement in work activities (paid or nonpaid) are associated with a reduction in both cognitive and non-cognitive achievements. Comparing the effect of young children's own time allocation with that of adolescents, he documents that the negative effect of time inputs in work in test scores is larger for the Younger Cohort than for the Older Cohort. Keane et al. (2018) focus on estimating cognitive ability production functions for a math and a verbal score, using the Younger Cohort data for the four countries. They document that leisure time is no more or less productive for child cognitive development than child work (including agricultural and paid work, as well as chores in the household).

On the consequences of child work, Bourdillon (2010) explains the importance of understanding child work holistically. While the work that children do is often seen as detrimental to their welfare, it may or may not interfere with school and schoolwork; it could be complementary in some cases, or it could provide the means to afford schooling. Some work activities could provide a different set of skills that prepare children for the economic environment in which they live. Therefore, child work can affect children's learning in both positive and negative ways. On this same vein, Vogler, Morrow and Woodhead (2009) argue that conceptualisation of child work as harmful often steams from normative idealised constructions of childhood that often do not reflect the local beliefs and values, and even less to the realities of children's lives and experiences, especially when applied to children in developing country contexts. Children engaging in low-intensive work and household production tasks is a widespread practice in developing countries and partly explains differences in their educational achievements (Seid & Gurmu, 2015). Cussianovich and Rojas (2014) report that for Peru, the incursion of rural children in household and work activities happens at an earlier age than in urban areas, yet school activities are the most valued by children and their families. More recently, Keane et al. (2018) show that both domestic chores and economic activities are detrimental to the development of cognitive skills (math and vocabulary), but only if they crowd out school time. The detrimental effect of work time is even greater if it crowds out time spent studying at home. Their finding holds for the four countries in the Young Lives study.

Also drawing on Young Lives data, Morrow and Boyden (2018) use descriptive information of children's working activities and qualitative experiences advocating for a more nuanced and

[44]See Caetano (2015) for a thorough discussion on the test.

comprehensive vision of child work. Likewise, Espinoza-Revollo and Porter (2018) offer a detail account of the evolving nature of time use during childhood and the influences that shape this process across the two Young Lives children cohorts.[45] Although failing to provide any causal explanation for child work (time use), they document important differences across countries, both in the amount of time children work and study. Gender matters for particular activities within the work aggregate. Girls do more housework and boys do more unpaid work in the household and paid work outside the household.

Haile and Haile (2012) study the determinants of work participation and school attendance of rural children aged 7 to 15; they find that the educational attainment (measured as grade for age) of working children decreases when they work long hours. Emerson, Ponczek and Souza (2017) find working while attending school translates up to a 13% decrease of a standard deviation in test scores for children in Brazil. The magnitude of the negative impact increases with student's ability, and lingering and cumulative negative effects persist from working while in school. Gunnarsson, Orazem and Sanchez (2006) use data from nine Latin American countries and find negative and significant effects of working on student test scores. As Emerson, Ponczek and Souza (2017) argue, the true nature of the connection between work and learning is one of substitutes or complements is still unclear. More empirical evidence is needed to examine this crucial relationship.

There is not much evidence on the effect of time spent in leisure for skills or learning. Using data from UK children between ages 3 to 5 years old (i.e. the Millenium Cohort Stud), Del Bono et al. (2016) document a positive relationship on recreational time in cognitive and non-cognitive skills. With Young Lives data, Borga (2018) finds a negative relationship (large and significant) for leisure activities and vocabulary ability for Ethiopia and leisure activities and Math score for India, when compared to time spent at school. Using time-use data for seven industrialised countries from the 1970s until 2000s, Gimenez-Nadal and Sevilla (2012) document a wide spread increase in leisure inequality in favour of lower educated adults. The relevance on this result is that these trends in leisure inequality mirror the general increase in income and earnings inequality experienced in most countries over this period, especially after the mid-1980s. Stiglitz, Sen and Fitoussi (2009) among others have recently proposed a broad range of measures of household economic activity to assess quality of life, including time spent in leisure activities.

[45]More information on the Young Lives data in chapter 1 and Section 3.3.

3.3 Data and Descriptive Statistics

As stated in chapter 1, the analyses on this chapter and chapter's 4, is based on data of the Young Lives study, focusing in Peru and the Younger Cohort. In particular, this chapter uses data from the last three survey rounds[46], when children were, on average 8 (2009), 12 (2012), and 15 years old (2016). In Peru, the sampling of the 20 clusters selected was at random, using districts as the unit sample frame. Then, within each cluster, 100 households with a child aged between 6 and 18 months were selected at random to participate in the study, excluding the richest 5% districts[47] (Escobal & Flores, 2008; Lives, 2018; Sanchez, 2017). The attrition rate for Peru is low compared to other longitudinal studies, only 8.2% for the Younger Cohort from the first (2002) to the fifth (2016) round, for the unweighted panel (Espinoza-Revollo & Porter, 2018). Our focus on the three last rounds of data follows three motivations. The first is that, from ages 8 to 15, the child undergoes through a critical development and transitional period from childhood to adolescence[48] which in turns highlights the importance for the key allocation of resources and time use by both parents and children. Second, there is less understanding about the dynamics and the importance each input represents during this transitional period than for instance early childhood.[49] Time use decisions might be influential for skill development as Keane et al. (2018) and Borga (2018) document using also Young Lives data. And third, to complement Espinoza-Revollo and Porter (2018) and expanding on Keane et al. (2018) and Borga (2018), I include time inputs from the last survey round (age 15) as part of the production functions for skill development.

Relevant information for the present analysis includes educational history on all household members, time use of household members aged 4 to 17 years old, child's cognitive tests, main caregiver and child's psychosocial measures, household socioeconomic circumstances (e.g. wealth index, information on economic shocks, food and non-food consumption and expenditure, etc.), health information of the child, and data on other measures (e.g. child's educational aspirations, parental expectations).

[46]In practice, I retain information of key variables from the first two rounds such as mother's age, main caregiver years of education, place of residence, if child was underweighted, and if child attended pre-primary education before aged 4-years-old.
[47]Young Lives is not intended to be a national representative survey, yet a comparison with the Demographic and Health Survey (DHS) 2000 at Round 1, showed that Young Lives sample covers the diversity of children and families in Peru. For more details on the sample design see Young Lives (2018), Cueto, Escobal, Penny and Ames (2011), and Escobal and Flores (2008).
[48]It represents a period where the prefrontal cortex starts to mature. The neuroplasticity of the adolescent brain allows for learning and unlearning behaviours, relevant for fostering psychosocial skills (Cunha et al., 2006).
[S]See Del Bono et al. (2016), Del Boca et al. (2016), Fiorini and Keane (2014) documenting the role of early time inputs during early childhood.

The unweighted Younger Cohort panel from Round 3 to Round 5 consists of 5,670 children-data points. From this sample:

1) I retain children with complete information on the time inputs (n = 5,544)
2) I retain children with complete information on the three outcomes (described in the following subsection), one cognitive skill and two psychosocial skills (n = 5,423)
3) I kept children with no missing information on a set of background variables including: child's sex, child's language, child's ethnicity, child's religion, indicators on child's underweight, birth order, information on pre-primary attendance, type of are (urban/rural) where family lived at Round 1, mother's age, main caregiver years of education, sex of household's head, level of expenditure in food and education items, and a wealth index (n = 5,134)

Finally, I retain children present at the last survey (Round 5), resulting in a period balanced sample of 5,034 children (exactly three observations for each child). The paired sample is the main analytic sample which fluctuates according to the modelling strategy and represents 89% of the unweighted sample.[50] To account for missing data and the loss of observations after imposing these restrictions, I construct Inverse Probability Weights (IP) and include them in the main analysis. In the Appendix, Figure B1 plots the relationship between the IP weights and the time inputs (hours per day at school, hours per day studying outside school, hours per day in leisure, and hours per day in child work); while Tables B2 and B3 compares means of the PPVT score, Self-Efficacy and Self-Esteem outcomes with and without imposing weights and differences in means between the Young Lives unweighted sample and the paired analytic sample, respectively. In next section I report descriptive statistics for the three outcomes, the time use measures and the control variables.

3.3.1 Child Outcomes

a. Cognitive Outcome: The Peabody Picture, and Vocabulary Test (PPVT)

The cognitive outcome is assessed through the Peabody Picture, and Vocabulary Test (PPVT) score at ages 5, 8, 12, and 15. It is a widely used test of receptive vocabulary, in which the level of difficulty varies according to the child's age. The test is composed of up to 204 items (125 in the Hispanic version, which was used in Peru), arranged in order of increasing difficulty and only the items within the critical range of the specific child were administered to each child, selected by the interviewer (Keane et al., 2018; Sanchez, 2017). The task of the examiner is to show a set of four pictures and ask the child to select the image that best

[50] The 11% reduction in sample size is smaller than other studies using the Peruvian Younger Cohort (e.g. Creamer (2016): 53%, Cueto et al. (2016): 31%), and studies examining time inputs and early child outcomes (e.g. Del Bono et al. (2016): 56%, Fiorini and Keane (2014): 88% for the last wave).

represents the word spoken by the examinee in their mother tongue (Cueto et al., 2016; Dunn, Padilla, Lugo, & Dunn, 1986). The PPVT was collected regardless of whether the child was attending school and also for a younger sibling.[51] I standardise scores to have mean zero and standard deviation of one for comparison. Keane et al. (2018) and Borga (2018), also use these outcomes as proxy for cognitive skill.

b. Psychosocial Measures: Self-Efficacy and Self-Esteem Index

I use two different indicators to examine psychosocial abilities for children, the Self-Efficacy and Self-Esteem Indexes.[52] The Self-Efficacy and Self-Esteem index are constructs based on respondents' degree of agreement or disagreement with a set of statements, five for both measures. Items and definitions used for each psychosocial measure are listed in Table 13. The degree of agreement is measured on a 4-point Likert scale ranging from strong agreement to strong disagreement. Both indexes are based on existing scales, with proper adjustment for child relevancy.

The Self-Efficacy Index builds on the Rotter scale and measures aspects associated to agency or "locus of control," assessing child's beliefs about the link between their behaviour and its consequences (Rotter, 1966). Previous research on "locus of control" or Self-Efficacy, have found associations between these measures and people's life choices (e.g. career decisions, investment in skills and education, earnings, etc.) (Coleman & DeLeire, 2003; S. Dercon & Krishnan, 2009; Maddux, 1991).

The Self-Esteem Index builds on the Rosenberg Self-Esteem scale measuring aspects related to pride and shame. The Young Lives adaptation focus more on specific dimensions of children's living circumstances (e.g. housing, clothing, work, school) (S. Dercon & Sanchez, 2013). The concept of Self-Esteem is also linked to a person's overall assessment of her own worth (Rosenberg, 1965). Borga (2018) and Krishnan and Krutikova (2013) use both indexes as proxies for psychosocial skills.

The two psychosocial measures were asked for the first time in Round 3, when children were about 8 years old. To construct the Self-Efficacy and Self-Esteem indexes, all relevant questions are normalised to *z-scores* and then an average of the relevant *z-scores* is taken across the non-missing values of the questions.[53] To measure the internal validity of the statements in Self-efficacy and Self-esteem indexes, Cronbach's Alphas are calculated to

[51] This is the main motivation on selecting the PPVT outcome as proxy for cognitive skill. In chapter 4 I take advantage of this information for the analysis.

[52] Young Lives also collected information for the child on the Life-satisfaction scale. I excluded it as part of the final analysis as a ceiling effect was consistently present on this outcome.

[53] I follow the same approach as Creamer (2016), Dercon and Sanchez (2013), Dercon and Singh (2013), and Dercon and Krishnan (2009). This approach recognises the existence of a latent variable that cannot be directly measured and hence try to approximate by an index of different dimensions related to Self-Efficacy/Agency and Self-Esteem (S. Dercon & Krishnan, 2009).

examine the interrelatedness of the scales. This exercise is useful per se, as the reliability of the scales has not been closely examined for the Younger Cohort psychosocial measures up to the last survey round.[54] A valid Cronbach's alpha is generally above 0.70 (Bland & Altman, 1997). For the analytic sample, Cronbach's alpha for Self-Efficacy is very low, just about 0.43; while for Self-Esteem is 0.60 (see Tables B4 and B5 in the Appendix). In their analysis on the internal validity of the psychosocial measures for the Older Cohort, Dercon and Krishnan (2009) discuss that Peru, among the countries of the Young Lives study, is the one with the lowest reliability on these measures. Potential reasons for this low reliability are a possible lack of understanding of these concepts in the Peruvian culture or the underlying multidimensionality.

Table 13. Psychosocial indicators*

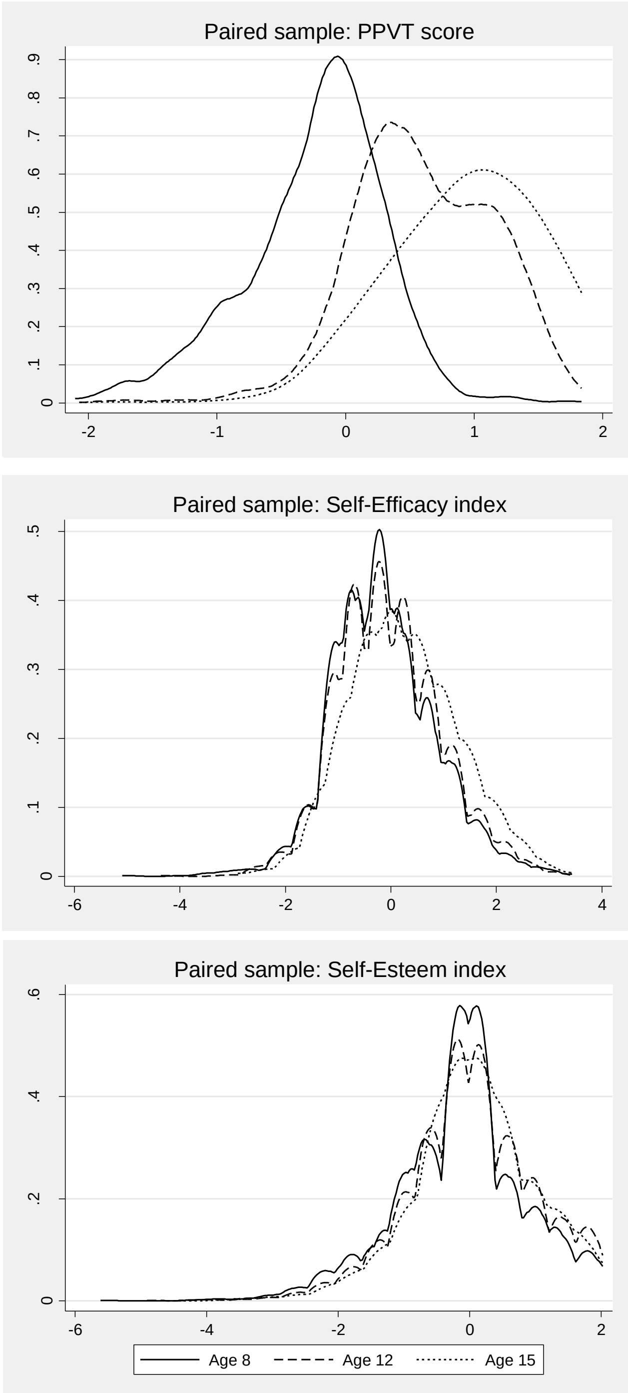
Measure	Question/Item
Self-efficacy index	If I try hard, I can improve my situation in life
	Other people in my family make all the decisions about how I spend my time [recoded to positive]
	I have no choice about the work I do—I must do this sort of work [recoded to positive]
	I like to make plans for my future studies and work
	If I study hard at school, I will be rewarded by a better job in the future
Self-esteem index	I am proud of my shoes or of having shoes.
	I am proud of my clothes
	I am never embarrassed because I do not have the right books, pencils or other equipment
	I am proud that I have the correct uniform
	I am proud of the work I have to do

*Adapted from Dercon and Singh (2013).

Figure 3 shows age-specific distributions of the standardised PPVT score, Self-Efficacy and Self-Esteem indexes, by each child's age. At age 8, the distribution of PPVT scores follows a normal distribution and as the child grows up, the distributions shift somewhat to the right. Distributions of Self-Efficacy Index are approximately normal across the three rounds, with longer tails in both sides. Regarding the Self-Esteem index, the distribution for the three rounds is slightly skewed to the right, with a longer tail in the left side of the distribution.

[54]Except for Creamer (2016) up to Round 4. Dercon and Krishnan (2009) examined the internal validity of Self-efficacy and Self-esteem for the Older Cohort in the four countries of the Young Lives study. Self-esteem measure proved reliable in three of the four countries, with a Cronbach's alpha near to 0.70, except for Peru, with a value of 0.50. Self-efficacy Cronbach's alpha was closer to 0.50, while for Peru it was 0.28.

Figure 3. Distribution of Standardised Outcomes by child age



*Note: Kernel density graphs for the three outcomes in Round 3 (Age 8), Round 4 (Age 12) and Round 5 (Age 15), following a normal distribution and bandwidth 0.35.

3.3.2 Time inputs

The time inputs measures were collected for all household members aged four to 17 years old at the moment of the survey. The present analysis takes advantage that for the period of interest, information of time use is reported directly from the child. Compared to most studies from developing countries, the information obtained in Young Lives data report the actual number of hours the child spends on different activities (Seid & Gurmu, 2015). These are child-specific time use daily measures (i.e. continuous variables), thus are easier to interpret, relative to studies using broader measures of home environment inputs (e.g. aggregate indexes) or binary indicators for child activities (Del Bono et al., 2016).

Children report time allocation as the total number of hours they spend on eight different activities on a typical weekday (Monday-Friday) when school was in session (i.e. excluding holidays, festivals, days of rest over the weekend) for the 24-hour budget-time (Briones, 2018). For the analysis, I comprise time use inputs into three broad categories. In practice, I examine the relationship of four time-inputs (listed in Table 14) within the three broad categories: 1) hours spent at school, 2) hours spent studying at home or outside school (both under the education category), 3) hours spent in leisure activities, and 4) hours spent in child work (an aggregate category that comprise four specific activities related to domestic or market work), with respect to time spent sleeping as the omitted category.

Table 14. Description of Time-inputs*

Category	Explanatory variable (Item)
Education	1. Number of hours per day the child spent at school (excluding travel time)
	2. Number of hours per day the child spent studying at home (including homework, extra classes, learning languages, and educational activities in general done outside the school)
Leisure	3. Number of hours per day the child spent in leisure activities (playing, seeing friends, using the internet, eating, drinking, bathing etc.)
Child work	4. Number of hours per day the child spent in child-working activities such as caring for others (caring for younger children or sick household members), 5. household chores (fetching water, cleaning, cooking, etc.), 6. domestic tasks (farming, herding, etc), and/or 7. Working outside household on paid activities.

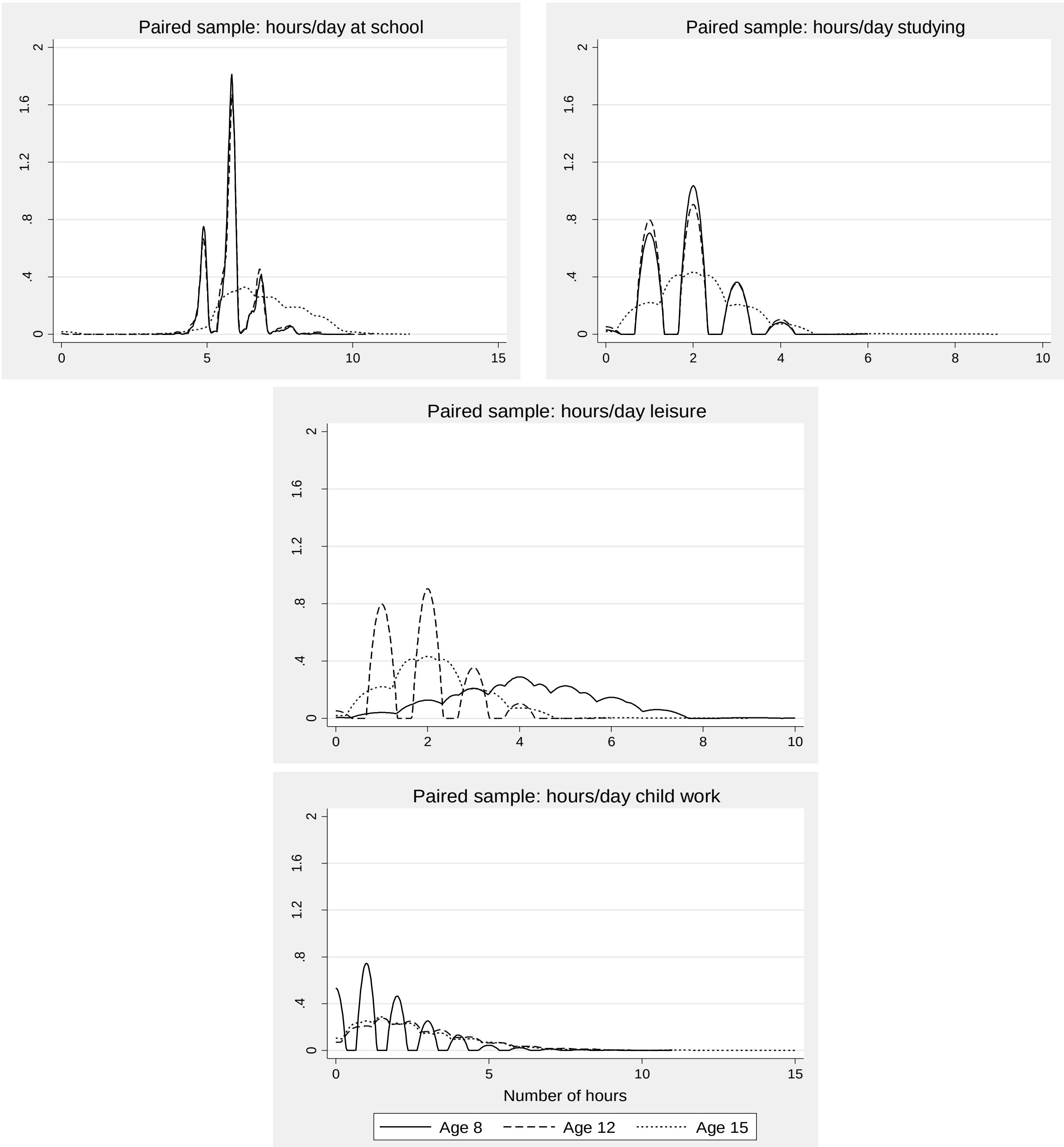
*The omitted category is time spent sleeping. One restriction on the leisure time inputs is the impossibility to disentangle the time spent in each individual activity defined as “leisure” in the questionnaire. The questionnaire instructs the interviewer to consider a wide range of activities spanning from playing or having fun with friends to daily routine/basic needs activities as eating or showering. A closer translation to this term could be spare-time.

Figure 4 shows the distributions for the time inputs of interest by age. For time spent at school, when children were about 8-years-old and 12-years-old, the distributions overlap as most of the sample spent about 6 hours on school. When they reach 15, the time spent at school increases[55], but the distribution flattens as it is also by this age when children transition to upper secondary, where it has been shown a critical grade at which children leave school (Espinoza-Revollo & Porter, 2018). For hours spent studying outside of school, distributions at the three rounds are somewhat similar, where children seem to allocate about 2 hours to this activity. Children spent more time in leisure activities at a younger age (8-years-old), about 4

[55]The normative shift length in Peru for Secondary level, between ages 12-16 years old, is seven hours per day.

hours, and as they get older, distribution shifts to the left for both ages (12 and 15), seeming to allocate about 2 hours less than in the previous round. Distribution for time spent in child work is skewed to the left, signalling that most of the children spent only a few hours (or zero) in any child work-related activity. This is most notorious for Round 3, when children were about 8-years-old.

Figure 4. Distribution of Time Inputs by child age



*Note: Kernel density graphs for the four-time inputs in Round 3 (Age 8), Round 4 (Age 12) and Round 5 (Age 15), following a normal distribution and bandwidth 0.35

Table 15 reports the mean and standard deviations for all three outcomes (standardised) and the time inputs in the paired analytic sample. As reported for the distributions above, it is not surprising that there is an increase in the number of hours spent at school and a slight increase on the time spent studying outside school as the child gets older. Children aged 8 and 12 spent around 6 hours at school and an extra hour (about 7 hours) by the time when they reach 15.[56] Surprisingly for child work, 12-years-old is the age where children spent more time in this type of activities, about 2.6 daily hours (156 min), while at 15, the time spent in child work amounts to 2.4 daily hours (144 min). Children aged 8-year-old spend less time in child work, about 1.5 hours (90 min) per day, though it means that they could spend up to 7.5 hours a week involved in any child work related activity.

Table 15. Means and Standard Deviations of Outcomes and Time Inputs

	Age 8	*Age 12*	*Age 15*
Outcomes			
PPVT score	-0.237 (0.546)	0.604 (0.550)	0.949 (0.532)
Self-Efficacy index	-0.134 (0.976)	-0.036 (0.979)	0.240 (1.00)
Self-Esteem index	-0.106 (1.009)	0.060 (0.999)	0.109 (0.916)
Time inputs			
Educational			
Hours/day spent at school	5.808 (0.708)	5.841 (0.774)	6.822 (1.525)
Hours/day spent studying outside school	1.896 (0.826)	1.851 (0.893)	2.134 (1.001)
Recreational			
Hours/day spent in leisure	4.107 (1.542)	3.641 (1.399)	3.378 (1.375)
Child work (aggregate)			
Hours/day spent in child work	1.574 (1.470)	2.599 (1.805)	2.367 (1.823)
Observations (N)	1678	1678	1678

*Table reports means and standard deviations in parentheses for the standardised outcomes and each of time inputs by age for the paired analytic sample (n = 5034).

3.3.3 Other variables

The analysis includes a rich set of child, parental, and household controls, some time-invariant and other time-variant. The time-invariant variables include: child's sex, birth order[57], child language, ethnicity, a set of dummies indicating region and area of birth, religion, a binary indicator whether the child attended pre-primary education by age 4, a binary indicator if child was underweighted, mother's age, and main caregiver's years of education. The time-variant controls include child's age (in months) at each round, number of siblings living in household

[56] The Ministry Education in Peru establishes mandatory full-time education for secondary level (ages 12 to 15/16) a shift of 35 weekly hours at school (seven hours of school per day).

[57] Including all siblings living in the household by Round 5, regardless if half-siblings (born from the mother or father).

aged 0 to 5 and aged 6-12, a household wealth index[58], monthly expenditure in education items[59], monthly household food expenditure[60], and an indicator if household head is female. Table 16 reports summary statistics for the control variables. The sample is balanced in terms of gender composition. More than 91 percent of the children is of Mestizo origin and profess Catholic faith (82%). Most of the children speak Spanish as the main language (87%) and lived in Urban areas (72%) at Round 1 of data collection. Also, only about 5% of the sample were underweight, while almost the full sample (95%) attended pre-primary education when they reached age 4. Mothers were on average 27 years old and main caregivers reported almost 8 years of education (equivalent to reaching eight-grade or having two years of secondary education) at Round 1.

Table 16. Summary Statistics of Control Variables[61]

	Mean	*SD*	*$SD_{between}$*	*SD_{within}*
Child Characteristics				
Age (in months)	138.941	34.94	4.996	34.659
Birth order (all siblings)	2.319	1.588	1.598	0.000
Female (prop.)	0.506	0.500	0.500	0.000
Children attended pre-primary (prop.)	0.949	0.219	0.227	0.000
Language is Spanish (prop.)	0.874	0.332	0.338	0.000
Religion is Catholic (prop.)	0.815	0.388	0.389	0.000
Other religion (prop.)	0.136	0.343	0.343	0.000
Ethnicity is Mestizo (prop.)	0.915	0.279	0.278	0.000
Ethnicity is White (prop.)	0.069	0.253	0.252	0.000
Child is underweight (prop.)	0.048	0.253	0.256	0.000
Household Characteristics				
Number of siblings aged 0-5 years old	0.534	0.724	0.54	0.486

[58]The household wealth index is composed of three sub-indexes: a) housing quality index, b) access to services index, and c) consumer durables index, all of which have equal weights in the estimation of the wealth index. It ranges from 0 (poorest) to 1 (less poor). Each sub-index was estimated consistently across rounds and only variables common to the four rounds were included. The housing quality sub-index is the average of the following dummy indicators: crowding, main material of walls, main material of roof, and main material of floor; the access to services sub-index is the averaged of the following dummy indicators: access to electricity, access to safe drinking water, access to sanitation, and access to adequate fuels for cooking: the consumer durables index is the average of a set of dummy variables denoting if a household member owns at least one of each consumer durable. The list of consumer durables included: radio, television, bicycle, motorbike, automobile, landline phone, mobile phone, refrigerators, stove, blender, iron, and record player (Azubuike & Briones, 2016; Briones, 2018).
[59]Education expenditure includes all money spent on school uniform for boys and girls, payments for tuition, fees or donations to school, books and stationary, and transport to school (Azubuike & Briones, 2016).
[60]Food expenditure represents the total monthly expenditure per capita in food consumption. It is constructed by aggregating all food items consumed in the last month from various sources: a) food purchased, b) food home-produced (own harvest), c) food items received as gifts or transfers, and d) food received from employers as payment in-kind for services rendered. The food reported as leftover was subtracted from the final aggregate (Azubuike & Briones, 2016).
[61]See Table B3 in the Appendix for summary statistics (difference in means) between the paired analytic sample and the observations excluded from the unweighted sample.

	Mean	*SD*	$SD_{between}$	SD_{within}
Number of siblings aged 6-12 years old	0.592	0.752	0.551	0.513
Wealth index	0.619	0.194	0.179	0.077
Monthly expenditure in education items per capita	15.962	22.761	18.761	12.776
Monthly expenditure in food items per capita	137.929	71.357	54.294	46.191
Parental Characteristics				
Mom age (at birth)	27.322	6.71	6.761	0
Caregiver years of education (at birth)	7.952	4.726	4.756	0
Head of household is female (prop.)	0.211	0.408	0.355	0.202
Region Characteristics				
Child lives in Coast region (prop.)	0.362	0.481	0.48	0
Child lives in Mountain region (prop.)	0.525	0.499	0.5	0
Child lives in Jungle region (prop.)	0.113	0.317	0.318	0
Child lives in Urban area (prop.)	0.725	0.446	0.449	0
Observations (Children)	1678			
Observations (Children-Data points)	5034			

[1]Minority category includes Native of the Amazon, Negro & Asiatic. [2]Wealth index ranges from 0 (poorest) to 1 (less poor) and is the average of housing quality, access to services, and consumer durables sub-indexes. [3]Food expenditure per capita available from Round 2 onwards, average reported here is from Round 2.

3.4 Empirical Estimation

As stated previously, estimating the relationship of different time inputs in the production of cognitive and psychosocial skills is problematic given the endogeneity of time inputs and the difficulty of measuring all relevant inputs to child development. I follow the approach developed by Todd and Wolpin (2007) and applied in time use related studies (Borga, 2018; D. Del Boca et al., 2014; Del Bono et al., 2016; Fiorini & Keane, 2014; Keane et al., 2018). As in Cunha and Heckman (2007, 2008), all these studies, and the present one, recognise skill formation as a life-cycle and cumulative process. The latter assumption implies that current and past inputs are combined with child's genetic endowment (unobserved ability) to produce a cognitive or psychosocial outcome.[62] The approach relates to the value-added literature in economics of education, employed to measure the role of school-level determinants (e.g. teacher effectiveness, class size, school autonomy) on educational achievement as function

[62]Ben-Porath (1967) was the first to model formally the production function framework as an individual choosing the level of time and resources to determine human capital investments. Leibowitz (1974) was the first to extend this conception to home investments in children. Since then, the production function approach has been used extensively in the literature of skills acquisition in economics (P. Todd & Wolpin, 2007).

of various inputs and a lagged outcome (Dearden et al., 2002 ; Hanushek, Rivkin, & Taylor, 1996; Jackson, 2018; Kane et al., 2008; Rivkin et al., 2005; Sass et al., 2014).

To explain the modelling strategy, I discuss the most general specification that nests other specifications in Equation (1). For simplification, I am assuming linearity in the production function for the skill Y, i.e. PPVT score, Self-Efficacy or Self-Esteem index, of child i observed at age α. Eq (1) becomes:

$$Y_{i\alpha} = \sum_{k=0}^{\alpha} \beta_{\alpha-k} T_{i,\alpha-k} + \sum_{k=0}^{\alpha} \delta_{\alpha-k} P_{i,\alpha-k} + \lambda Y_{i,\alpha-k} + \epsilon_{i,\alpha} \quad (1)$$

Where i indexes the child, $T_{i,\alpha-k}$ represents the vector of educational, leisure and child work time inputs, $P_{i,\alpha}$ represents the vector of parental, child, and household characteristics[63] (see Section 3.3.4), and $\epsilon_{i,\alpha}$ is an error term capturing shocks in the child life-cycle, unobserved inputs (e.g. innate ability or endowments), and measurement error (e.g. in skill test or time inputs). $\beta_{\alpha-k}$ is our coefficient of interest. Eq (1) allows the full history of observed time inputs to affect child skills (including current and past time inputs). Moreover, including one-period lagged outcome ($Y_{i,\alpha-1}$) (e.g. past PPVT score/Self-Efficacy/Self-Esteem Index) captures self-productivity[64] or outcome persistence, and proxies for the stock of "all" previous inputs (observed and unobserved) into the production of cognitive and psychosocial outcomes (Del Bono et al., 2016; Fiorini & Keane, 2014; P. Todd & Wolpin, 2003). Eq (1) is known as the cumulative value-added (CVA) model[65] and comprises most of the common specifications found in the akin literature, including the ones employed in the present study. Thus, if $\lambda = 0$ and the influence of all past inputs is set to zero, $Y_{i\alpha}$ is assumed to depend exclusively on current (age α) time and observable inputs ($T_{i,\,\alpha}$ and $P_{i,\,\alpha}$), where $P_{i,\,\alpha}$ reduces omitted variable bias. Consistent estimates of β_{α} are only achieved if omitted factors are orthogonal to the time inputs included. The latter specification represents the contemporaneous model (CT) and I will use the estimates as benchmark to compare the "improvements" of the subsequent specifications. The main problem with CT is simultaneity or reverse causality, as both inputs and outcomes are measured at the same age of the child. The latter is of less concern in the present study as I am not using this specification to answer the main research question,

[63]The vector of time-invariant predictors include child's sex, birth order, child's language, ethnicity, region and area of residence at Round 1, religion, whether the child was severely or moderately underweight at Round 1, whether the child attended pre-primary education before aged 4, mother's age, main caregiver years of education; and the vector of time variant predictors include child's age in months, number of siblings living in household aged 0 to 12, a household wealth index, level of food and education expenditure per capita (in *Soles*), if family head is female and village fixed effects.
[64]As defined by Cunha and Heckman (2007) as one of the skills properties in the technology of skill formation model.
[65]Using cross-validation methods, Todd and Wolpin (2007) selected this specification, among competing specifications, to study the sources of test score gaps (determinants of cognitive achievement) between black, white, and Hispanic children.

comparing the relevance of earlier time inputs relative to later time inputs (e.g. two-period lagged time inputs($T_{i,\alpha-2}$) versus one-period lagged inputs ($T_{i,\alpha-1}$), or one-period lagged inputs ($T_{i,\alpha-1}$) versus contemporaneous time inputs ($T_{i,\alpha}$) into the production of current PPVT score and Self-Efficacy/Self-Esteem indexes ($Y_{i\alpha}$). The second specification relaxes the assumption that only current time inputs ($T_{i,\alpha}$) matter and includes the vector of observable lagged inputs ($T_{i,\alpha-k}$ and $P_{i,\alpha-k}$). As in CT, it holds the assumption that any omitted inputs and endowments are orthogonal to the time inputs included and does not consider the effect of past outcomes ($\lambda = 0$) (P. Todd & Wolpin, 2007). This specification is known as the cumulative model (CU) and I estimate two versions for the analysis. One including one-period lagged time inputs ($T_{i,\alpha-1}$); and a second one, extending the influence in outcomes of two-period lagged time inputs ($T_{i,\alpha-2}$).

Alternatively, if $\beta_{\alpha-k} = \beta_0 = 0$ and $\delta_{\alpha-k} = \delta_0 = 0$, then Eq (1) converts into the value-added model (VA).[66] It expands the CT specification by including one-period lagged outcome ($Y_{i,\alpha-1}$) as proxy for unobserved innate ability. The main assumptions in this case are that the effect of inputs (observed or unobserved) ($T_{i,\alpha-k}$ and $P_{i,\alpha-k}$) declines with age at the rate λ_α (assumed to be the same for each input); also, the impact of endowment (innate ability) declines at the same rate as input effects.[67] This assumption is relaxed in the cumulative value-added specification (CVA) when historical data of time inputs is included ($\beta_{\alpha-k} \neq 0$ and $\delta_{\alpha-k} \neq 0$), besides the lagged outcome ($\lambda \neq 0$). A common issue in VA and CVA modelling is that measurement error $\epsilon_{i,\alpha}$ diminishes λ, also affecting input coefficients (β and δ). A standard approach implemented under this framework, contingent on data availability, is instrumenting the one-period lagged outcome ($Y_{i,\alpha-1}$) with the two-period lagged outcome ($Y_{i,\alpha-2}$) (Anderson & Hsiao, 1981; Arellano & Bond, 1991; Del Bono et al., 2016). Then the CVA model transforms into the cumulative value-added instrumental variables model (CVA-IV) model.

As summarised in Del Bono, et al. (2016) and Fiorini and Keane (2014), the issue of endogeneity has three potential causes. One is omitted variable bias (including unobserved child endowments or unobserved inputs). An attempt to deal with this issue is to estimate several specifications with different assumptions (as discussed above) and using very rich longitudinal data (e.g. using CU, CVA and CVA-IV models). A second cause is reverse causality. To illustrate this issue, consider a child with innate cognitive ability who enjoys spending more time studying outside of school and achieving a higher test score; or a child

[66]Excluded in the present analysis as effectively, two VA extended versions (CVA and CVA-IV) are included and the main interest is to examine the role of time inputs within the VA framework.
[67]For a more thorough discussion on the assumptions and restrictions in each model, see Todd and Wolpin (2007).

with innate higher cognitive ability even if spending less time studying, still gets a higher test score than a child with less cognitive endowment and who spends more hours studying. A solution to this problem is to account for unobserved innate ability by including past skill test outcomes using the CVA specification and including additional proxies in vector $P_{i,\alpha}$ to help capture omitted inputs. Recent studies offer supportive evidence on the effectiveness of the lagged test score as a control for unobserved heterogeneity (Deming, Hastings, Kane, & Staiger, 2014; Guarino, Reckase, & Wooldridge, 2014). Moreover, as the CVA model might respond to feedback or adjustment effects (e.g. shifts on current parental decisions/investments respond to past outcomes), I implement the CVA-IV specification. A third cause of endogeneity is measurement error in both input measures and/or outcomes. An example of measurement error in inputs is if the parent or main caregiver does not know exactly how much time children spend in each specific activity. I address this concern by taking advantage of using own's child reports on how they allocate their time, although I do not argue the approach eliminates measurement error completely, given also the limitations of the time inputs measures, discussed in Section 3.3. The issue on measurement error in outcomes is more problematic. I partially address the problem of measurement error in one-period lagged outcome ($Y_{i,\alpha-1}$) using as instrument the two-period lagged outcome ($Y_{i,\alpha-2}$) in the CVA-IV model.[68] Yet, self-reported measures (including child's time inputs reports and the Self-Esteem and Self-Efficacy items) have a strong likelihood of inherent error component to them. The psychosocial measures deserve special attention given the observed low levels of Cronbach's alpha, particularly for the Self-Efficacy Index. In addition, there is a strong likelihood that $\epsilon_{i,\alpha}$ will be negatively correlated with the lagged skill test outcome ($Y_{i,\alpha-k}$) if the latter contains measurement error, biasing the λ estimate downwards and β_α in ambiguous directions (Keane et al., 2018). The potential impact of measurement error varies under different assumptions. For the present analysis, I only assume classical measurement error. If classical measurement error is only present in the variable of interest (e.g. time inputs), this will influence the size of the coefficients of interest (e.g. attenuation bias)[69]. Using CVA and CVA-IV specifications for the main analysis attempts to deal with this bias. Furthermore, as part of the robustness checks, I estimate *Hybrid* specifications of the production function and within child-fixed effects. Their advantages and limitations are discussed in Section 3.6.

[68]As part of the robustness exercises, I also instrument one-period lagged cognitive (psychosocial) outcome with a one-period or two-period lagged psychosocial (cognitive) outcomes (e.g. one-period lagged PPVT instrumented with one-period or two-period lagged Self-Efficacy or Self-Esteem).

[69]According to O'Neill and Sweetman (2012), non-classical measurement error might arise if there is a relationship between the reported measurement error and the true value of the variable of interest (e.g. time inputs); secondly, it would also be present if there is a relationship between the reported measurement error and the residual in Eq (1). The latter situation is referred to as differential measurement error; in this case, time inputs contain information about our outcome of interest, and even after we condition on time inputs, none of the approaches will yield consistent estimates (D. A. Black, Berger, & Scott, 2000).

3.5 Results

This section compares estimates among the different specifications listed above: the CT, two CU models (using one-lagged and two-period lagged time inputs), the CVA, and the CVA-IV model. As the CVA-IV specification is the most time input intensive (extending the influence of all-period time inputs into the skill outcome) and dealing with measurement error for the one-period lagged outcome, we argue for now that this is our preferred specification. Time inputs coefficients are interpreted relative to time spent sleeping, the omitted category.

3.5.1 Cognitive Skill: The Peabody Picture Vocabulary Test (PPVT)

Table 17 below reports the time inputs coefficients for all model specifications derived from Eq (1), five regressions in total, and pooling all ages together. Hence, outcomes indicate the influence in PPVT score at age 15 as a function of current and past inputs. Column 1 shows estimates for the contemporaneous specification (CT), i.e. outcome regressed on the inputs and other controls at age 15, Columns 2 and 3 report coefficients for the cumulative specifications (CU), including time inputs at the same age and one (CU_{t-1}) or two-period lags (CU_{t-2}) of time inputs. Column 4 presents estimates from the cumulative value-added (CVA) model, where besides lagged time inputs, it includes one-period lagged PPVT score (dependent variable). Finally, Column 5 includes the CVA-IV model, instrumenting one-period lagged PPVT score (age 12) with two-period lagged PPVT score (age 8), dealing with measurement error concerns (Andrabi, Das, Khwaja, & Zajonc, 2011; Arellano & Bond, 1991; Del Bono et al., 2016).

In general, the influence of daily time inputs (current and historical) is small (CVA) or has no effect (CVA-IV) in the production of the PPVT score. The time inputs effects are stronger when not accounting for the past PPVT score. When considering the information on past time inputs (Columns 2 and 3), the influence of present and past time inputs becomes stronger, particularly for educational time inputs. This result suggests that excluding historical time inputs leads to an understatement of the immediate impact of a unit increase in time inputs (Del Bono et al., 2016). Time inputs effects diminish significantly or fade out when estimating the CVA and CVA-IV specifications. The specific results are as follow:

If only current inputs matter ($\lambda = 0$, $\beta_{\alpha-1} = 0$, $\beta_{\alpha-2} = 0$), an additional hour spent in educational activities (i.e. at school plus studying outside school) per day barely increases the PPVT score by 0.033[= *hours at school*: 0.024 (age 15) + *hours studying*: 0.009 (age 15)] of a standard deviation at age 15 (significant at the 5%). For Column 3 (CU_{t-2}), one hour increase in each lagged educational time input (hours spent at school and hours spent studying outside school) at ages 8 and 12, increases the PPVT score at age 15 by 0.119 s.d. [= *hours at school*:

0.024 (age 12) + 0.018 (age 8) + *hours studying* (0.040 (age 12) + 0.037 (age 8)]. In this case, both period-lagged educational inputs ($\beta_{\alpha-k}$), 0.064 s.d. for age 12 and 0.055 s.d. for age 8, have almost the same influence on current PPVT score. Although the effect of lagged hours spent studying is stronger than that of the number of hours spent at school. The results also show that spending one hour working at age 8 ($\beta_{\alpha-2}$), can lead to a decrease of the PPVT score of 0.020 s.d. by age 15; in contrast, spending time in leisure activities at ages 8 and 12, increases the PPVT score by 0.022 s.d. (joint effect).

If time inputs effects were already small, coefficients of all educational time inputs decline substantially for the CVA specification (Column 4) and fade out for the CVA-IV model (Column 5) when accounting for the lagged PPVT score. In both models, we can observe that the role of the past PPVT score is substantial in the prediction of the current PPVT score, ranging from 0.499 (Column 4) to 0.992 s.d (Column 5) when using two-period lagged PPVT score (age 8) as instrument. These results confirm the existence of outcome persistence, where past educational time inputs contribute on the subsequent production of the PPVT score. They are also consistent with the results obtained when inspecting the correlation of the PPVT score with time (in Table B6 in the Appendix) and when looking at the first-stage results for the CVA-IV model (in Table B10 in the Appendix). A differing result shows for time spent in leisure, being positive at age 8 (0.011 s.d.) for the CVA model and negative for current leisure time (-0.010 s.d.) in the CVA-IV model, but in both cases the magnitude of the time input coefficient is small. On child work time inputs, the relationship is negative (small in magnitude) and not significant for the CVA and CVA-IV models.

Besides using the two-period lagged PPVT score as instrument for the one-period lagged in the main results (Column 5), I follow previous studies (Del Bono et al., 2016) and conduct alternative CVA-IV specifications, instrumenting the one-period lagged PPVT score with one-period or two-period lagged Self-Efficacy and Self-Esteem Indexes, individually or both. Two-period lagged Self-Efficacy (age 8) alone proved not to be a valid instrument. When using all two-period lagged outcomes (Self-Efficacy, Self-Esteem, and PPVT score at age 8) as instruments, the negative coefficients in hours spent at school (age 8), current and one-period lagged time spent in leisure (ages 15 and 12), and current time spent in child work increase and become statistically significant. This result might be hinting into some complementary among the three skills to influence PPVT score at age 15. For the rest of the instruments checks, time inputs results are qualitatively similar, and the effect of the lagged outcome (after instrumenting) ranges from 1.171 to 0.832, all significant at 5% or 1% levels. First-stage results using the alternative instruments and estimates of time inputs are reported in Tables B11 and B14 in the Appendix.

Table 17. Time Inputs for PPVT score

	Benchmark (CT) (1)	CU_{t-1} (2)	CU_{t-2} (3)	CVA (4)	CVA-IV (5)
Education Time Inputs					
Hrs/day at school	0.024**	0.033***	0.032***	0.017***	0.002
	(0.011)	(0.006)	(0.007)	(0.006)	(0.007)
Hrs/day at $school_{t-1}$		0.017*	0.024*	0.008	-0.008
		(0.008)	(0.012)	(0.010)	(0.011)
Hrs/day at $school_{t-2}$			0.018***	0.014**	0.010
			(0.005)	(0.005)	(0.008)
Hrs/day studying outside school	0.009	0.029***	0.033***	0.020***	0.007
	(0.029)	(0.006)	(0.007)	(0.006)	(0.007)
Hrs/day studying outside $school_{t-1}$		0.040***	0.040***	0.026***	0.012
		(0.008)	(0.008)	(0.007)	(0.008)
Hrs/day studying outside $school_{t-2}$			0.037***	0.015	-0.007
			(0.010)	(0.009)	(0.011)
Leisure Time Inputs					
Hrs/day in leisure activities	-0.001	0.005	-0.001	-0.006	-0.010*
	(0.008)	(0.006)	(0.006)	(0.005)	(0.006)
Hrs/day in leisure $activities_{t-1}$		-0.000	0.010*	0.003	-0.003
		(0.004)	(0.006)	(0.005)	(0.006)
Hrs/day in leisure $activities_{t-2}$			0.012***	0.011**	0.010
			(0.004)	(0.005)	(0.006)
Child work Time Inputs					
Hrs/day in child work	-0.002	-0.001	-0.002	-0.002	-0.001
	(0.011)	(0.005)	(0.005)	(0.004)	(0.004)
Hrs/day in child $work_{t-1}$		-0.014***	-0.004	-0.007	-0.009
		(0.003)	(0.006)	(0.005)	(0.006)
Hrs/day in child $work_{t-2}$			-0.020***	-0.006	0.007
			(0.006)	(0.005)	(0.006)
PPVT $score_{t-1}$				0.499***	0.992***
				(0.031)	(0.042)
R-squared	0.717	0.700	0.477	0.601	0.480
RSS	374.676	795.409	501.692	382.620	498.987
p-value $H_0: \beta_n = \beta_{n\alpha-k} = 0$	0.426	0.098	0.028	0.069	0.106
Observations	6,503	4,826	3,044	3,044	3,044

***p<0.01, **p<0.05, *p<0.1. Clustered robust standard errors in parentheses at the village level. Each column presents a separate regression, using inverse probability weights. Controls include (reported in Table B7 in the Appendix) time-invariant predictors (child's sex, birth order, child's language, ethnicity, region and area of residence at Round 1, religion, whether the child was severely or moderately underweight at Round 1, whether the child attended pre-primary education before aged 4, mother's age, main caregiver years of education; and time variant predictors (child's age in months, number of siblings living in household aged 0 to 12, a household wealth index, level of food and education expenditure per capita (in *Soles*), if family head is female) and village fixed effects. Reference categories: (Child's sex) Female, (Language) Other, (Birth order) First-born, (Underweight) Not underweighted (Ethnicity) Mestizo (includes Native of the Amazon, Negro & Asiatic), (Religion) Catholic, (Language) Other (Area) Urban, (Region) Coast.

3.5.2 Psychosocial Skills: Self-Efficacy and Self-Esteem

I now turn to the main results for the psychosocial skills, reported in Table 18 for the Self-Efficacy Index and Table 19 for the Self-Esteem Index. For the Self-Efficacy Index, current time inputs in education and child work (age 15) and one-period lagged time inputs in education (age 8) matter and their influence is slightly larger than in the PPVT outcome. Moreover, controlling for the lagged Self-Efficacy outcome (age 12) in Column 4 (CVA), does not attenuate time inputs coefficients, in contrast to the PPVT results. When estimating the CVA-IV model (Column 5), we notice the estimate for the one-period lagged Self-Efficacy (after instrumenting with the two-period lagged outcome) is very imprecise (huge standard errors)[70] and all the time inputs effects dissipate. Investigating into the first-stage estimates (reported in Table B10, we notice poor explanatory power among all time inputs (exogenous variables) and the coefficient for the two-period lagged Self-Efficacy Index is positive, small in magnitude and not statistically significant. In this case, the CVA-IV model produces biased estimates and should not be considered. Turning then to the CVA estimates (Column 4), adding two extra hours in current educational time inputs, one hour spent at school and one hour spent studying at age 15, can lead to an increase in the Self-Efficacy Index of 0.115 s.d at the same age 15. This is independent of the influence of one-period lagged educational inputs (time spent at school and studying at age 12), which amounts to an increase of 0.136 of s.d. There is also a negative effect on time spent in child work at age 15, where any extra hour devoted to child work activities decreases the Self-Efficacy index by 0.052 s.d. The coefficient on the lagged Self-Efficacy index indicates mild outcome persistence, where one-unit increase in the Self-Efficacy index at age 12, leads to an increase in the Self-Efficacy index at age 15 by 0.177 s.d (not as large as in the PPVT score).

Several explanations of the source of bias when implementing CVA-IV include that estimates might be suffering from larger small-sample bias (Cameron & Trivedi, 2009), the twice-lagged Self-Efficacy Index (age 8) is not a valid instrument, and/or overall measurement error of this outcome (given the low Cronbach alpha observed and reported in Table B4). Further investigation on the extent of measurement error is needed. When checking for alternative instruments, the first-stage results indicate that only one (age 12) and two-period lagged (age 8) PPVT score have predictive power as instruments, being positive and statistically significant (see Table B12 in the Appendix)[71], but none of the time inputs coefficients have explanatory power. These results confirm that CVA-IV is not a valid specification to estimate the production function for the Self-Efficacy outcome and, more important, this outcome is likely to be plagued of measurement error since it was first collected. Even for the rest of the specifications, results should be taking cautiously. Time-inputs estimates for the CVA-IV model using the alternative instruments are reported in Table B15 in the Appendix.

[70]Notice also the R-squared is not possible to estimate under this model.
[71]There is also one specification largely imprecise, instrumenting one-period lagged Self-Efficacy with two-period lagged Self-Esteem.

Table 18. Time Inputs for Self-Efficacy index

	Benchmark (CT) (1)	CU_{t-1} (2)	CU_{t-2} (3)	CVA (4)	CVA-IV (5)
Education Time Inputs					
Hrs/day at school	0.044***	0.041***	0.036**	0.034***	0.024
	(0.015)	(0.014)	(0.014)	(0.012)	(0.036)
Hrs/day at school$_{t-1}$		0.017	0.068**	0.059*	-0.017
		(0.013)	(0.031)	(0.030)	(0.129)
Hrs/day at school$_{t-2}$			-0.005	-0.009	-0.040
			(0.029)	(0.028)	(0.085)
Hrs/day studying outside school	0.054**	0.051**	0.081***	0.081***	0.082
	(0.019)	(0.020)	(0.026)	(0.024)	(0.058)
Hrs/day studying outside school$_{t-1}$		0.036**	0.082***	0.077***	0.029
		(0.016)	(0.023)	(0.023)	(0.096)
Hrs/day studying outside school$_{t-2}$			-0.009	-0.021	-0.132
			(0.031)	(0.027)	(0.178)
Leisure Time Inputs					
Hrs/day in leisure activities	-0.003	-0.005	0.003	0.004	0.015
	(0.014)	(0.014)	(0.020)	(0.020)	(0.036)
Hrs/day in leisure activities$_{t-1}$		0.022***	0.013	0.012	0.001
		(0.007)	(0.018)	(0.020)	(0.042)
Hrs/day in leisure activities$_{t-2}$			0.022	0.014	-0.055
			(0.021)	(0.020)	(0.113)
Child work Time Inputs					
Hrs/day in child work	-0.035***	-0.035***	-0.050***	-0.052***	-0.074
	(0.011)	(0.010)	(0.016)	(0.015)	(0.051)
Hrs/day in child work$_{t-1}$		-0.011	-0.001	-0.000	0.009
		(0.010)	(0.017)	(0.018)	(0.039)
Hrs/day in child work$_{t-2}$			-0.005	-0.003	0.015
			(0.018)	(0.018)	(0.056)
Self-Efficacy$_{-1}$				0.181***	1.767
				(0.014)	(2.684)
R-squared	0.131	0.133	0.168	0.195	N.A.
RSS	4317	4246	1358	1315	4659
p-value $H_0: \beta_n = \beta_{n\alpha-k} = 0$	0.000	0.005	0.008	0.014	0.793
Observations	4,962	4,898	1,626	1,626	1,626

***p<0.01, **p<0.05, *p<0.1. Clustered robust standard errors in parentheses at the village level. Each column presents a separate regression, using inverse probability weights. Controls include (reported in Table B8 in the Appendix) time-invariant predictors (child's sex, birth order, child's language, ethnicity, region and area of residence at Round 1, religion, whether the child was severely or moderately underweight at Round 1, whether the child attended pre-primary education before aged 4, mother's age, main caregiver years of education; and time variant predictors (child's age in months, number of siblings living in household aged 0 to 12, a household wealth index, level of food and education expenditure per capita (in *Soles*), if family head is female) and village fixed effects. Reference categories: (Child's sex) Female, (Language) Other, (Birth order) First-born, (Underweight) Not underweight (Ethnicity) Mestizo (includes Native of the Amazon, Negro & Asiatic), (Religion) Catholic, (Language) Other (Area) Urban, (Region) Coast. For column 5, R-squared is not reported (negative value) and cannot be recovered from estimation output.

For the Self-Esteem results (in Table 19), there is no effect on time inputs across all specifications, except for time spent in leisure activities at age 15 and time spent in child work at age 8. Any extra hour spent daily in leisure activities leads to a decrease of 0.059 s.d. in the Self-Esteem index at age 15, for both CVA (Column 4) and CVA-IV models (Column 5). There is also a negative relationship between Self-Esteem and time in child work at age 8, where one hour spent per day at that age leads to a decrease of more than 0.040 s.d. by age 15 for models in Columns 3 (CU), 4 (CVA) and 5 (CVA-IV). As with the Self-Efficacy results, controlling for the lagged Self-Esteem index does not affect the magnitude of time inputs coefficients. Furthermore, one unit increase in the past Self-Esteem index leads to an increase of the current Self-Esteem index of 0.182 s.d., only for the CVA (Column 4) model. The influence disappears when instrumenting the one-period lagged Self-Esteem (age 12) index with the two-period lagged (age 8) outcome, although the estimate is also very imprecise (i.e. large standard error). Inspecting into the first-stage results (see Table B10 in the Appendix), we notice the two-period lagged Self-Esteem index does not have explanatory power for the one-period Self-Esteem index (e.g. the coefficient is small in magnitude, positive, and not statistically significant), making it an invalid instrument. When investigating with alternative instruments, only one-period lagged Self-Efficacy index had statistical explanatory power; and most of the time inputs coefficients are insignificant except for time spent in leisure activities at age 15, which aligns with the main CVA-IV results in Column 5 (see Table B13 for first stage results and Table B16 for time inputs coefficients with alternative instruments in the Appendix).

Table 19. Time Inputs for Self-Esteem index

	Benchmark (CT) (1)	CU_{t-1} (2)	CU_{t-2} (3)	CVA (4)	CVA-IV (5)
Education Time Inputs					
Hrs/day at school	0.020 (0.019)	0.018 (0.019)	0.007 (0.017)	0.007 (0.015)	0.008 (0.017)
Hrs/day at school$_{t-1}$		0.029** (0.012)	0.022 (0.037)	0.020 (0.036)	0.022 (0.036)
Hrs/day at school$_{t-2}$			0.013 (0.040)	0.005 (0.041)	0.013 (0.057)
Hrs/day studying outside school	0.017 (0.017)	0.015 (0.018)	0.022 (0.028)	0.017 (0.027)	0.023 (0.032)
Hrs/day studying outside school$_{t-1}$		0.018 (0.020)	0.024 (0.027)	0.028 (0.026)	0.024 (0.032)
Hrs/day studying outside school$_{t-2}$			-0.031 (0.034)	-0.040 (0.033)	-0.030 (0.061)
Leisure Time Inputs					
Hrs/day in leisure activities	-0.041*** (0.014)	-0.041*** (0.014)	-0.059*** (0.018)	-0.057*** (0.018)	-0.059*** (0.019)
Hrs/day in leisure activities$_{t-1}$		-0.012 (0.011)	-0.001 (0.024)	0.007 (0.023)	-0.002 (0.034)
Hrs/day in leisure activities$_{t-2}$			-0.011 (0.018)	-0.012 (0.018)	-0.011 (0.019)
Child work Time Inputs					
Hrs/day in child work	-0.007 (0.012)	-0.008 (0.012)	-0.020 (0.013)	-0.023* (0.012)	-0.020 (0.013)
Hrs/day in child work$_{t-1}$		-0.008 (0.009)	-0.001 (0.015)	-0.001 (0.015)	-0.001 (0.015)
Hrs/day in child work$_{t-2}$			-0.043** (0.018)	-0.040** (0.017)	-0.043* (0.022)
Self-Esteem$_{-1}$				0.168*** (0.023)	-0.018 (0.724)
R-squared	0.080	0.083	0.090	0.120	0.083
RSS	4400	4331	1238	1197	1248
p-value $H_0: \beta_n = \beta_{n\alpha-k} = 0$	0.003	0.352	0.047	0.038	0.004

	Benchmark (CT) (1)	CU_{t-1} (2)	CU_{t-2} (3)	CVA (4)	CVA-IV (5)
Observations	4,963	4,899	1,626	1,626	1,626

***p<0.01, **p<0.05, *p<0.1. Clustered robust standard errors in parentheses at the village level. Each column presents a separate regression, using inverse probability weights. Controls include (reported in Table B9 in the Appendix) time-invariant predictors (child's sex, birth order, child's language, ethnicity, region and area of residence at Round 1, religion, whether the child was severely or moderately underweight at Round 1, whether the child attended pre-primary education before aged 4, mother's age, main caregiver years of education; and time variant predictors (child's age in months, number of siblings living in household aged 0 to 12, a household wealth index, level of food and education expenditure per capita (in *Soles*), if family head is female) and village fixed effects. Reference categories: (Child's sex) Female, (Language) Other, (Birth order) First-born, (Underweight) Not underweighted (Ethnicity) Mestizo (includes Native of the Amazon, Negro & Asiatic), (Religion) Catholic, (Language) Other (Area) Urban, (Region) Coast.

3.5.3 Discussion: Cognitive Skills vs. Psychosocial Skills

It is unclear to what extent the issue on measurement error regarding the Self-Efficacy Index is biasing the time inputs estimates for that outcome. Hence, I will focus the discussion comparing the PPVT and Self-Efficacy results. Overall, time inputs effects are marginal for both types of skills with important differences in the type of activities influencing each outcome, hinting that the production functions for each skill are different. When comparing the coefficients, and excluding the CVA-IV estimates for now, results for time inputs coefficients are robust and fairly consistent across the different models for the PPVT score. Focusing on the CVA specification and relative to time spent sleeping, time inputs in educational activities, both past (i.e. time spent studying at age 12 and time at school at age 8) and present (age 15), are more productive for the PPVT score, leading to an increase of up to 0.077 s.d. [= *hours at school*: 0.017 (age 15) + 0.014 (age 8) + *hours studying*: 0.020 (age 15) + 0.026 (age 12)] by age 15. Any extra hour spent studying per day is slightly more productive than daily extra hours spent at school. These results confirm the hypothesis that time-inputs in educational activities are positively more productive for cognitive skills, in this case, the verbal outcome, and are in line with previous studies (Borga, 2018; Keane et al., 2018). There is no evidence that time spent in child work is harmful for the PPVT score.

For the Self-Esteem Index, current (age 15) and past (age 8) time spent in child work, and present (age 15) time spent in leisure, is detrimental for this skill at age 15, relative to time spent sleeping. Any extra hour spent in leisure and any extra hour spent in child work, decreases the Self-Esteem Index by 0.057 (age 15) and 0.063 s.d. [= *hours in child work*: 0.020 (age 15) + 0.043 (age8)], respectively. These results confirm the initial hypothesis on the negative relationship between child work time-inputs and psychosocial skills but are in contrast with the "expected" positive relationship between leisure inputs and the production of psychosocial skills. The negative result for leisure inputs may have two possible explanations. On the one hand, it might show that any additional extra hour spent in leisure activities is not enough to be satisfied with it, craving for more time on these activities, affecting Self-Esteem levels. On the other hand, it might indicate that time inputs captured under the "leisure" umbrella, are more related to routine activities such as eating, drinking, bathing, and these actions are being perceived as "obligations" rather than leisure time. Unfortunately, is impossible to disentangle the actual time distribution among each leisure activity.

A sizeable difference among both skills is the influence the lagged outcome (i.e. PPVT score or Self-Esteem index at age 12) has on the outcome of interest by age 15. When controlling for the past outcome, time inputs effects are considerable diminished or fade out for the PPVT score, while for the Self-Esteem Index are virtually unchanged. Though outcome persistence is strong for the PPVT score, accounting at least for 50% of current PPVT score (0.499 s.d.) in the CVA model[72], is significantly less for the Self-Esteem index, only about 17% (0.168 s.d.). This result is consistent with the notion of differences in malleability among types of skills and at different ages. Previous studies indicate that malleability is greater for cognitive skills at early ages (0 to 6 years-old) and then becomes stable. In contrast, malleability is higher for psychosocial skills during adolescence, where interventions have proved successful to influence behaviour (Cunha et al., 2006). Another aspect to consider is that, time inputs coefficients might be suffering of small-sample bias from the 2SLS estimator when implementing the CVA-IV approach, more evident for the Self-Esteem and Self-Efficacy Indexes (large standard errors) as having less observations for these indicators.

Although time inputs effects might seem small, it is important to not forget that coefficients represent incremental (diminishments) from any daily extra hour devoted to each activity in a regular school/working day. Transforming to weekly estimates, and assuming a constant behaviour on the reported daily time allocation, time inputs in present and past educational activities could increase the PPVT score at age 15 by 0.385 s.d. [= 0.077 x 5(1 hour per working day, Mon-Fri)]. For the Self-Esteem Index, the decrease of current time spent in leisure and past and present time in child work could amount to a decrease of 0.305 s.d. and 0.335 s.d., respectively. However, we are less confident on the Self-Esteem escalated weekly estimates, given the malleability property of this skill during this period and evident on the main results. The weekly time inputs are larger in magnitude to the ones observed for developed economies, as in Fiorini and Keane (2014).

3.6 Further Evidence

This section adds on the time inputs evidence as follows. First and given the policy interest on the negative consequences of chid work, I examine the trade-offs between child work and the rest of the time activities into the skills production function. Second, and probing on the

[72]As expected, the lagged test score increases when we instrument for it (CVA-IV), reaching almost 100% (0.992 s.d) of the PPVT score value.

robustness of the main results, I analyse the role of missed inputs on skills by estimating two hybrid production functions, adding inputs that were excluded from the main specification. One of the hybrid specifications examines the role of the main caregiver's own psychosocial measures (Self-Esteem and Self-Efficacy) and whether the child is enrolled in a private school. The other hybrid specification investigates the role of income, controlling for the fact that the mother was working Full-time when the child was between 6-18 months to 5 years-old[73] and the incidence of monetary shocks related with mother or father illness. Finally, controlling for unobservable characteristics that are fixed over time (and exploiting variation that occurs within families), I estimate within child fixed-effects (FE) models. This is a popular approach used in the economics literature to purge of any time-invariant unobserved heterogeneity (alternative to the CVA specification that includes the lagged outcome to account for heterogeneity). Adding this empirical strategy serves to further check the robustness of the main results and model strategies.

3.6.1 Child work and skills

In this section, I expand the analysis on the role of time spent in child work and how it affects positively (negatively) the PPVT score and the Self-Esteem Index, using only the CVA and CVA-IV specifications.[74] I investigate if there is a trade-off between hours spent in child work and the rest of time inputs for a subsample of children that reported at least one hour per day spent in child work and that are currently enrolled in school (see Table B17 for the sample distribution). I do this by expanding the child work category into each of the specific child work tasks[75] and switching the omitted category in each regression, so the effect of child work (and the rest of the time input coefficients) can be interpreted as crowding-out time spent in the omitted time-input category in turn. As stated in Emerson, Ponczek and Souza (2017), the direction of the expected effect of child work on learning is still unclear. On the one hand, working requires time and energy that could curb the child's ability to learn. On the other hand, some of the child work related activities could involve tasks directly or indirectly related to learning. The recent study from Keane, Krutikova, and Neal (2018) using Young Lives data, finds that the negative influence on child work (paid activities) for cognitive outcomes only holds if it crowds-out time spent studying. Adding to these results using the last survey round from Young Lives, Tables 20 and 21 reports coefficients only for time inputs in child work for

[73]Age information available specifically for Round 1 and Round 2. Effectively, the indicator denoting Full-time working status was coded as 1 if at any of these two Rounds the mother reported to be in Full-time working.
[74]For the PPVT score I estimate both specifications. For the Self-Esteem, I only conduct the CVA one, given the small-sample bias concerns exposed in the previous section.
[75]Listed in Table 2: time spent in care activities, household chores, household tasks, and paid work activities.

the PPVT score and the Self-Esteem Index, respectively. The rest of time inputs estimates are reported in Tables B18 and B19 in the Appendix.

For the PPVT score, the detrimental effects of time spent in child work are small in magnitude and vary by age and the specific task. Current time (age 15) spent in paid work exhibits a consistent negative influence in both CVA and CVA-IV specifications. The coefficient is greater when it crowds-out time spent at school or time spent studying, decreasing the PPVT score between 0.030 s.d. and 0.037 s.d. in the CVA and CVA-IV specifications, respectively. Yet, there is also evidence of positive effects in time spent in paid work at age 12 and they are about the same size effect (0.025-0.031 s.d.). There is also mild evidence of the negative influence on hours spent in household chores at age 12, leading to a decrease in the verbal score of 0.020 s.d., but only for the CVA specification.

As in the main results, there is no trade-off effect of any of the child work activities for the Self-Esteem Index (i.e. outcome remains insensitive to time inputs). In contrast, there is evidence of detrimental effects if substituting current time (age 15) spent in leisure instead of studying or time at school. The decrease for the Self-Esteem Index for any extra hour spent in leisure oppose to any of the educational activities could amount up to 0.059 s.d. (See Table B19 in the Appendix).

Table 20. Child work trade-offs: PPVT score

		CVA			**CVA-IV**	
Omitted category:	Leisure (1)	School (2)	Study (3)	Leisure (4)	School (5	Study (6)
Child Work Time Inputs						
Hrs/day care activities	0.009	0.003	0.003	0.008	0.004	0.003
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Hrs/day care activities$_{t-1}$	-0.006	-0.006	-0.009	-0.006	-0.007	-0.009
	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
Hrs/day care activities$_{t-2}$	0.001	0.003	0.003	0.014	0.016	0.017
	(0.011)	(0.011)	(0.011)	(0.010)	(0.011)	(0.011)
Hrs/day household chores	-0.000	-0.007	-0.005	0.004	0.000	-0.001
	(0.009)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)
Hrs/day household chores$_{t-1}$	-0.020*	-0.019*	-0.020*	-0.006	-0.007	-0.009
	(0.011)	(0.010)	(0.010)	(0.006)	(0.007)	(0.007)
Hrs/day household chores$_{t-2}$	-0.020*	-0.017	-0.016	-0.001	0.003	0.004
	(0.011)	(0.011)	(0.011)	(0.013)	(0.013)	(0.012)
Hrs/day household tasks	0.005	-0.001	-0.000	0.016	0.012	0.011
	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.011)
Hrs/day household tasks$_{t-1}$	-0.015	-0.014	-0.019	-0.014	-0.014	-0.018
	(0.013)	(0.012)	(0.012)	(0.015)	(0.014)	(0.015)
Hrs/day household tasks$_{t-2}$	-0.023*	-0.020	-0.021	-0.007	-0.004	-0.002
	(0.013)	(0.013)	(0.013)	(0.014)	(0.015)	(0.014)
Hrs/day paid work	-0.024*	-0.032**	-0.030**	-0.033**	-0.036**	-0.037***
	(0.012)	(0.013)	(0.012)	(0.015)	(0.016)	(0.014)
Hrs/day paid work$_{t-1}$	0.031**	0.031**	0.025*	0.035***	0.034***	0.031***
	(0.012)	(0.012)	(0.012)	(0.011)	(0.011)	(0.011)
Hrs/day paid work$_{t-2}$	0.070	0.073	0.061	0.042	0.047	0.040
	(0.063)	(0.064)	(0.058)	(0.059)	(0.059)	(0.056)

Omitted category:	CVA Leisure (1)	School (2)	Study (3)	CVA-IV Leisure (4)	School (5	Study (6)
PPVT score$_{t-1}$	0.489***	0.493***	0.491***	0.994***	0.992***	0.989***
	(0.031)	(0.030)	(0.031)	(0.046)	(0.042)	(0.045)
R-squared	0.593	0.592	0.591	0.467	0.468	0.470
p-value $H_0: \beta_n = \beta_{n\alpha-k} = 0$	0.002	0.004	0.018	0.052	0.000	0.000
Observations	2,759	2,759	2,759	2,759	2,759	2,759

***p<0.01, **p<0.05, *p<0.1. Clustered robust standard errors in parentheses at the village level. Each column presents a separate regression, omitting the time input in the title and using inverse probability weights. Controls include time-invariant predictors (child's sex, birth order, child's language, ethnicity, region and area of residence at Round 1, religion, whether the child was severely or moderately underweight at Round 1, whether the child attended pre-primary education before aged 4, mother's age, main caregiver years of education; and time variant predictors (child's age in months, number of siblings living in household aged 0 to 12, a household wealth index, level of food and education expenditure per capita (in *Soles*), if family head is female) and village fixed effects. Reference categories: (Child's sex) Female, (Language) Other, (Birth order) First-born, (Underweight) Not underweighted (Ethnicity) Mestizo (includes Native of the Amazon, Negro & Asiatic), (Religion) Catholic, (Language) Other (Area) Urban, (Region) Coast.

Table 21. Child work trade-offs: Self-Esteem

Omitted category:	CVA Leisure (1)	School (2)	Study (3)
Child Work Time Inputs			
Hrs/day care activities	-0.000	-0.024	-0.024
	(0.023)	(0.025)	(0.025)
Hrs/day care activities$_{t-1}$	-0.027	-0.029	-0.031
	(0.019)	(0.021)	(0.021)
Hrs/day care activities$_{t-2}$	-0.037	-0.035	-0.037
	(0.033)	(0.031)	(0.032)
Hrs/day household chores	0.022	-0.003	-0.001
	(0.028)	(0.028)	(0.028)
Hrs/day household chores$_{t-1}$	0.009	0.006	0.007
	(0.022)	(0.022)	(0.023)
Hrs/day household chores$_{t-2}$	-0.031	-0.029	-0.028
	(0.036)	(0.040)	(0.040)
Hrs/day household tasks	-0.019	-0.043	-0.043
	(0.025)	(0.025)	(0.029)
Hrs/day household tasks$_{t-1}$	0.010	0.010	0.005
	(0.020)	(0.023)	(0.022)
Hrs/day household tasks$_{t-2}$	0.005	0.006	0.003
	(0.024)	(0.025)	(0.022)
Hrs/day paid work	0.057	0.034	0.034
	(0.044)	(0.042)	(0.045)
Hrs/day paid work$_{t-1}$	-0.017	-0.020	-0.026
	(0.035)	(0.037)	(0.039)
Hrs/day paid work$_{t-2}$	0.164	0.154	0.141
	(0.484)	(0.474)	(0.476)
Self-Esteem$_{t-1}$	0.027	0.033	0.039
	(0.041)	(0.041)	(0.046)
R-squared	0.077	0.081	0.080
p-value $H_0: \beta_n = \beta_{n\alpha-k} = 0$	0.241	0.004	0.025
Observations	2,757	2,757	2,757

***p<0.01, **p<0.05, *p<0.1. Clustered robust standard errors in parentheses at the village level. Each column presents a separate regression, omitting the time input in the title and using inverse probability weights. Controls include time-invariant predictors (child's sex, birth order, child's language, ethnicity, region and area of residence at Round 1, religion, whether the child was severely or moderately underweight at Round 1, whether the child attended pre-primary education before aged 4, mother's age, main caregiver years of education; and time variant predictors (child's age in months, number of siblings living in household aged 0 to 12, a household wealth index, level of food and education expenditure per capita (in *Soles*), if family head is female) and village fixed effects. Reference categories: (Child's sex) Female, (Language) Other, (Birth order) First-born, (Underweight) Not underweighted (Ethnicity) Mestizo (includes Native of the Amazon, Negro & Asiatic), (Religion) Catholic, (Language) Other (Area) Urban, (Region) Coast.

3.6.2 Hybrid specifications

According to Todd and Wolpin (2007) and Del Bono et al. (2016), an option to adjust for missing inputs information is to substitute input demand equations in place of the unobserved inputs. In this case, missing inputs are functions of current and past family income, prices and preferences shocks. Variables related to family income and preferences, such as mother's employment status, main caregiver's psychosocial skills, shocks related to a family member illness, etc., are then included in the new estimation. A crucial assumption for the "hybrid" specification is to impose a non-zero correlation between observed included inputs and the unobservable drivers of child skill development, dealing with the potential issue that the "hybrid" specification might be picking-up preference parameters and not just the technology of child development (Del Bono et al., 2016; Ermisch & Francesconi, 2013). I proceed to estimate two hybrid production functions, that besides including the inputs from the main results, they encompass additional inputs excluded from Eq (1). For both "hybrid" estimations, I report CVA and CVA-IV specifications for the PPVT score and the CVA for the Self-Esteem index. The new variables added for the *Hybrid 1* function are the own psychosocial measures of the mother/main caregiver (Self-efficacy and Self-esteem indexes)—assuming main caregivers with a higher set of psychosocial skills have a technological advantage in the production of their child's skills—(Creamer, 2016; S. Dercon & Singh, 2013; P. Todd & Wolpin, 2007); and a binary indicator denoting if the child was enrolled in private versus public school. These extra inputs are all time-variant (to capture their cumulative effect and to allow for heterogeneity in how they affect each outcome with respect to the child's age). For the *Hybrid 2* function, I account for mother's working status[76] when the child was still young (between 6-18 months and 5 years-old) and the presence of monetary shocks related with mother or father illness throughout the life-cycle. The first additional input is time-invariant, while the second is time-variant. Table 22 below reports the summary statistics of the *Hybrid* controls for the paired

[76]Information on mother working status was coded using a subsection for the main caregiver on working activities. The questionnaire asked for information related to the three main working activities. I created a binary indicator, coded 1 to denote Full-Time working status or 0 otherwise. For Round 2, I assigned Full-Time working status if the aggregate number of hours for one, two or the three activities together, added 8 or more hrs per day. For Round 1, I considered as Full-Time working status if in the original categorical variable of number of days worked per week, main caregiver answered 6 to 7 days a week.

sample. About 12% of the sample reported to suffer from a monetary shock, due to an illness of the mother or father.

Table 22. Summary Statistics of *Hybrid* controls

	Mean	*SD*	*SD$_{between}$*	*SD$_{within}$*
Main caregiver Self-Efficacy Index	0.002	1.009	0.572	0.834
Main caregiver Self-Esteem Index	0.014	0.989	0.626	0.769
Child enrolled in private school (prop.)	0.186	0.389	0.318	0.221
Household suffered monetary shock due to mother/father illness (prop.)	0.123	0.328	0.189	0.270
Main Caregiver Full-Time work (prop.)	0.545	0.498	0.498	0.000
Observations (Children)	1,147			
Observations (Children-Data points)	4,295			

*Note: After restricting the estimation to the paired sample, the number of observations for both *Hybrid* specifications is fewer than from the main results (Tables 5 and 7). For *Hybrid 1*-PPVT (CVA-IV), the total number of children-data points is 3,002 (42 observations less than in the main results). For *Hybrid 1*-Self-Esteem (CVA-IV), the total number of children-data points is 1,616 (only 10 observations less than in the main results). For Hybrid 2, the loss of observations is larger given the limited availability on working status data for the main caregiver in the initial two rounds. The total number of children-data points for Hybrid 2-PPVT (CVA-IV) is 2067, while for Hybrid 2-Self-Esteem (CVA-IV) is 1,111. Both sample sizes represent 68% of the paired analytic sample from the main results for their respective specification.

Overall, results for both *Hybrid* models confirm the robustness of the main results to the inclusion of additional inputs as coefficients remain virtually unchanged (Table 23).

For *Hybrid 1*, the positive influence of current and past educational inputs (Column 1) and the negative relationship with current time spent in leisure (Column 2) for the PPVT score remains the same. For the Self-Esteem Index, the detrimental effect of current time spent in leisure is attenuated but only by 0.006 s.d. (i.e. 0.055 s.d. instead of 0.061 s.d. from the main results).

For *Hybrid 2*, the effect of educational inputs for the PPVT score becomes stronger in the CVA model (Column 4) and even the coefficient of time spent studying at age 8 turns significant in the CVA-IV (Column 5), opposite to the main results. The negative effect of current time spent in leisure (age 15) is marginally enhanced for the PPVT outcome (Columns 4-5), while attenuated for the Self-Esteem Index (Column 6). Each difference only represents less than 0.014 s.d., being this value, the largest difference observed (i.e. for time spent studying at age 8 for the CVA-IV model). Furthermore, only the coefficient for the binary indicator on private school enrolment and the Self-Esteem index of the main caregiver are positive and significant for the PPVT score and the Self-Esteem Index, respectively.

Table 23. Hybrid Specifications[77]

	Hybrid 1			*Hybrid 2*		
	PPVT (CVA)	**PPVT (CVA-IV)**	**Self-Esteem (CVA)**	**PPVT (CVA)**	**PPVT (CVA-IV)**	**Self-Esteem (CVA)**
	(1)	(2)	(3)	(4)	(5)	(6)
<u>*Education Time Inputs*</u>						
Hrs/day at school	0.015**	0.000	0.010	0.015*	-0.005	0.010
	(0.006)	(0.008)	(0.015)	(0.008)	(0.011)	(0.018)
Hrs/day at school$_{t-1}$	0.006	-0.007	0.026	0.021	0.001	0.023
	(0.010)	(0.011)	(0.038)	(0.013)	(0.015)	(0.043)
Hrs/day at school$_{t-2}$	0.014**	0.012	0.009	0.020***	0.014	-0.014
	(0.005)	(0.007)	(0.041)	(0.006)	(0.009)	(0.051)
Hrs/day studying outside school	0.019***	0.006	0.020	0.018*	0.002	-0.009
	(0.006)	(0.007)	(0.028)	(0.009)	(0.011)	(0.037)
Hrs/day studying outside school$_{t-1}$	0.025***	0.012	0.027	0.035***	0.026**	0.019
	(0.007)	(0.008)	(0.026)	(0.009)	(0.011)	(0.028)
Hrs/day studying outside school$_{t-2}$	0.013	-0.009	-0.038	0.002	-0.020	-0.031
	(0.010)	(0.012)	(0.034)	(0.010)	(0.013)	(0.036)
<u>*Leisure Time Inputs*</u>						
Hrs/day in leisure activities	-0.007	-0.012**	-0.055***	-0.012*	-0.016**	-0.047**
	(0.005)	(0.006)	(0.018)	(0.006)	(0.008)	(0.020)
Hrs/day in leisure activities$_{t-1}$	0.003	-0.003	0.009	0.006	0.001	-0.000
	(0.005)	(0.006)	(0.023)	(0.005)	(0.006)	(0.026)
Hrs/day in leisure activities$_{t-2}$	0.011**	0.010	-0.009	0.009	0.008	-0.030
	(0.005)	(0.006)	(0.019)	(0.006)	(0.008)	(0.023)
<u>*Child Work Time Inputs*</u>						
Hrs/day in child work	-0.003	-0.003	-0.020	-0.003	-0.003	-0.028
	(0.003)	(0.003)	(0.012)	(0.006)	(0.006)	(0.017)
Hrs/day in child work$_{t-1}$	-0.006	-0.009	-0.002	-0.004	-0.008	0.008
	(0.004)	(0.006)	(0.015)	(0.006)	(0.007)	(0.012)
Hrs/day in child work$_{t-2}$	-0.006	0.007	-0.040**	-0.008	0.004	-0.030
	(0.006)	(0.006)	(0.017)	(0.005)	(0.006)	(0.019)
Outcome$_{t-1}$	0.500***	0.985***	0.166***	0.475***	0.951***	0.135***
	(0.031)	(0.041)	(0.023)	(0.034)	(0.053)	(0.026)
R-squared	0.598	0.478	0.127	0.631	0.523	0.128
p-value $H_0: \beta_n = \beta_{n\alpha-k} = 0$	0.058	0.107	0.037	0.009	0.020	0.168
Observations	3,002	3,002	1,616	2,067	2,067	1,111

***p<0.01, **p<0.05, *p<0.1. Clustered robust standard errors in parentheses at the village level. Each column presents a separate regression, using inverse probability weights. For Columns 3-4 and 7-8 controls are as in footnote of Tables 5 and 7. For Columns 1-2, besides main results controls, additional predictors include the Self-Efficacy and Self-Esteem indexes (z-scores) of main caregiver and if child was enrolled in private school. For Columns 5-6, besides main results controls, additional predictors include if main caregiver was working Full-Time for Round 1 and/or Round 2 of data collection, and if the family experienced any monetary shocks due to illness of the mother or father.

3.6.3 Fixed-Effects

A popular empirical approach to control for time-invariant unobserved heterogeneity is within child fixed-effects (FE). This specification exploits variation that occurs within families, in this case, within children across different ages. The FE estimator is feasible given the

[77]I matched the sample size of the paired analytic sample from the main results to the Hybrid sample to make valid comparisons. Even when not adjusting to the same number of observations, results remain qualitatively the same.

longitudinal nature of the Young Lives data (i.e. having multiple observations on outcomes and inputs for a given child at different ages). For this specification, one takes differences across time, as shown in Equation (2).

$$\Delta Y_{i\alpha} = \Delta \sum_{k=0}^{\alpha} T_i \, \beta + \Delta \sum_{k=0}^{\alpha} P_{i,\alpha} \, \delta \, + \Delta\lambda Y_{i,\alpha-1} + \Delta\epsilon_{i,\alpha} \qquad (2)$$

To estimate consistent parameters of Equation (2), the main assumptions in this model include: (a) the impact of endowments on outcome of interest ($Y_{i\alpha}$) must be independent of age (differencing eliminates unobserved endowments from Eq (2)), (b) the choices on later inputs are invariant to prior child's outcomes, (c) the differenced inputs included in the estimation are orthogonal to the omitted differenced inputs and their effect is constant with age (hence eliminated by the differencing).

There are two disadvantages of this estimator. The first one relates to measurement error. If the data on outcomes is afflicted with measurement error (as we suspect at least for the Self-Efficacy Index), the issue on attenuation bias for lagged-outcomes increases. The second one is that the FE estimator does not allow to identify whether the effects of observed inputs change over the child's life cycle and whether past idiosyncratic individual shocks affect current input decisions (Del Bono et al., 2016). The latter limitation explains why the FE estimation is excluded from the main analysis section and used instead as a robustness check.

Table 24 reports results for the FE model. We notice FE estimates almost mirrors results obtained from the CVA specifications for all outcomes (Column 5 in Tables 5-7). For the PPVT score, the positive effect for current and past educational time inputs (i.e. current time spent at school and studying outside (age 15), and the two-period lagged time spent at school (age 8) remains the same. The negative effect of current time spent in child work (age 15) sustains for the Self-Efficacy index and extends to the one-period lagged estimate (age 12); while the detrimental effect of current time spent in leisure (age 15) for the Self-Esteem index albeit diminished, also prevails. Perhaps what stands out as the main difference is the opposite (and negative) relationship with the lagged outcome, while being positive for the main results. Nevertheless, FE estimates adds on to the robustness of the time inputs coefficients obtained in the CVA main results.

Table 24. Fixed-Effects

	PPVT	**Self-Efficacy**	**Self-Esteem**
	(1)	(2)	(3)
Education Time Inputs			
Hrs/day at school	0.015**	0.018	0.019
	(0.007)	(0.021)	(0.021)
Hrs/day at school$_{t-1}$	0.014	0.028	0.019
	(0.013)	(0.035)	(0.033)
Hrs/day at school$_{t-2}$	0.012*	-0.031*	0.026

	PPVT	Self-Efficacy	Self-Esteem
	(1)	(2)	(3)
	(0.006)	(0.018)	(0.020)
Hrs/day studying outside school	0.007	0.035	0.028
	(0.009)	(0.035)	(0.036)
Hrs/day studying outside school$_{t-1}$	0.020*	(0.035)	(0.034)
	(0.011)	(0.035)	(0.035)
Hrs/day studying outside school$_{t-2}$	0.022**	0.038	0.031
	(0.011)	(0.035)	(0.037)
Leisure Time Inputs			
Hrs/day in leisure activities	-0.006	0.011	-0.040**
	(0.007)	(0.021)	(0.020)
Hrs/day in leisure activities$_{t-1}$	-0.011	0.026	0.007
	(0.007)	(0.023)	(0.023)
Hrs/day in leisure activities$_{t-2}$	-0.004	0.020	0.006
	(0.005)	(0.016)	(0.016)
Child work Time Inputs			
Hrs/day in child work	-0.002	-0.055***	-0.017
	(0.006)	(0.018)	(0.017)
Hrs/day in child work$_{t-1}$	0.006	-0.068***	-0.008
	(0.007)	(0.022)	(0.021)
Hrs/day in child work$_{t-2}$	-0.004	-0.030	-0.028
	(0.007)	(0.020)	(0.020)
Outcome$_{t-1}$	-0.385***	-0.417***	-0.412***
	(0.040)	(0.022)	(0.022)
R-squared	0.540	0.284	0.239
p-value $H_0: \beta_n = \beta_{n\alpha-k} = 0$	0.328	0.006	0.083
Observations	3,146	3,146	3,146

***p<0.01, **p<0.05, *p<0.1. Clustered robust standard errors in parentheses at the village level. Each column presents a separate regression. Controls include (reported in Table A12 in the Appendix) time variant predictors (child's age in months, number of siblings living in household aged 0 to 12, a household wealth index, level of food and education expenditure per capita (in *Soles*), an indicator if family head is female), village and child fixed effects.

3.6.4 Discussion: Further Evidence

This section started examining the trade-off of child work against the rest of the time inputs and how they influence the production of PPVT score and Self-Esteem outcomes. We find only small detrimental effects of current time spent in paid work (age 15), particularly when it crowds-out time spent in educational activities for the PPVT score; and no child work related effects for the Self-Esteem Index. We do confirm the negative effects of current time spent in leisure, specifically when it crowds-out time inputs on education. The magnitude of the effect is larger on decreasing the Self-Esteem Index (0.059 s.d.), than the one observed for paid work on decreasing the PPVT score (0.030 s.d.) (see Tables B18 and B19). This result has important implications when thinking about earlier studies claiming negative effects in child work. As pointed out by Keane, Krutikova and Neal (2018), it is essential to consider which is the actual counterfactual time activity that the child should reallocate her/his efforts that fosters the increase on cognitive and psychosocial skills. Having information for the full-time budget of the child (24 hours), gives us a comparative advantage to investigate the trade-off more accurately than in previous investigations. Furthermore, the disaggregated information on the different time inputs in child work allows us to identify which specific type of child work policies should target to enhance human capital accumulation in adolescence.

Evidence from the *Hybrid* specifications and the Fixed-effects strategy confirm the robustness of the estimates obtained in the main results. Accounting for missing inputs strengthens the positive effect of time spent in educational activities for the PPVT score, while marginally attenuating the detrimental effects of current time spent in leisure. Dealing with unobserved heterogeneity, the FE estimates mirror the main results obtained with the CVA specifications. They confirm the positive effect for current and past educational time inputs for the PPVT score; and for the Self-Esteem index, the negative effect of current time spent in child work (age 15), and the detrimental effect of current time spent in leisure (age 15). The main difference with this strategy is the negative relationship with the lagged outcome, while being positive for the main results (CVA). Likewise, it is unclear if attenuation bias worsens if the outcomes are measured with error. While we do not have concerns for the verbal score, we are not 100% sure for the Self-Esteem measure. Still, evidence into the causal mechanisms on how to foster psychosocial skills is very limited. The negative result of time spent in leisure for the Self-Esteem Index is consistent with the findings from Borga (2018) for the Older Cohort in Vietnam and Ethiopia (using the three previous rounds of data).

3.7 Conclusions

This study examined the relationship between children time inputs and the production functions of cognitive and psychosocial skills, employing rich longitudinal survey data from Peru, a country with persistent inequalities.

Overall, time inputs effects are marginal for both types of skills, but we document important differences in the type of activities influencing each outcome by age, confirming that the production functions for each skill are different, as hypothesised in the introduction and established in previous studies (Cunha & Heckman, 2008; Del Bono et al., 2016).

Throughout different specifications (i.e. CVA, FE), our results show that time in educational activities, such as the time spent studying and at school during the school-age period and when transitioning into adolescence is crucial for verbal (cognitive) development. Relative to time spent sleeping, past (i.e. time studying at age 12 and time at school at age 8) and present time inputs in educational activities are more productive for the PPVT score at age 15, leading to an increase of up to 0.077 s.d. These same results indicate that an extra hour spent studying per day is slightly more productive than extra daily hours spent at school. When using the two-period lagged PPVT score (age 8) as an instrument to account for the potential measurement error in one-period lagged PPVT score (i.e. CVA-IV), time inputs effects in education fade out. However, when using alternative instruments, specifically when instrumenting the one-period lagged PPVT outcome with the Self-Efficacy, Self-Esteem, and PPVT score at age 8, findings show a negative coefficient in hours spent at school (age 8), current and one-period lagged time spent in leisure (ages 15 and 12), and current time spent in child work increase and become statistically significant. The latter might be hinting into some complementary among the three skills to influence PPVT score at age 15. On the trade-off analysis of child work, we only find small detrimental effects of current time spent in paid work (age 15), particularly when it crowds-out time spent in educational activities for the PPVT score.

For the Self-Esteem Index, current time spent in leisure and past (age 8) and present time spent in child work is detrimental for this skill at age 15, relative to time spent sleeping. The decrease amounts between 0.057 and 0.63 s.d, respectively. An important finding for the Self-Esteem index is the consistent detrimental effect of current time (age 15) spent in leisure across different empirical strategies (i.e. CVA, FE), when estimating alternative specifications to account for missing inputs, and when analysing the trade-off and contribution of each time input activity into each skill. Unfortunately, we are not able to disentangle which are the specific leisure activities driving the negative result, as opposed when we examined the trade-offs in child work. This is a relevant issue given the broad range of activities classified as “leisure” in the questionnaire, spanning from playing or having fun with friends to daily routine/basic needs activities as eating or showering.

One difference among both skills is the influence of the lagged outcome when the child is in mid-adolescence by age 15. Controlling for the past outcome, time inputs are considerably diminished or fade out for the PPVT score, while for the Self-Esteem Index are virtually unchanged. This result is consistent with the notion of differences in malleability among types of skills and at different ages. Previous studies indicate that malleability is greater for cognitive skills at early ages (0 to 6 years old) and then becomes stable. In contrast, malleability is higher for psychosocial skills during adolescence, where interventions have proved successful in influencing behaviour (Cunha et al., 2006).

An important consideration relates to the measurement error evident on the Self-Efficacy Index, pushing us to exclude the estimates in the discussion; and the small-sample bias issue from the 2SLS estimator when implementing the CVA-IV strategy for the Self-Esteem Index, which in turn made us focus on the CVA estimates for this skill. Greater efforts should be implemented in studies validating, collecting and measuring psychosocial skills. This is crucial if we aim to document the causal processes and mechanisms for skill formation in these types of skills, and also relevant to the design of developmentally timed interventions. There are still a lot of unknown questions to be answered related to the development and malleability of psychosocial skills along the life-cycle, and how they interact and complement with cognitive skills. The latter implies a closer collaboration among disciplines, particularly the economics and psychology fields.

The findings for the PPVT outcome confirm the initial hypothesis that time-inputs allocated to educational activities are positively more productive for cognitive skills and are in line with previous investigations (Borga, 2018; Keane et al., 2018). With respect to the psychosocial indicators, the results confirm the initial hypothesis on the negative relationship between child work time-inputs and the formation of psychosocial skills but are in contrast with the “expected” positive relationship between leisure time-inputs and the production of psychosocial skills. The negative result for leisure inputs may have two possible explanations. On the one hand, it might show that any additional extra hour spent in leisure activities is not enough to be satisfied with it, craving for more time on these activities, affecting Self-Esteem levels. On the other hand, it might indicate that time inputs captured under the “leisure” umbrella, are more related to routine activities such as eating, drinking, bathing, and these actions are being perceived as “obligations” rather than leisure time. Unfortunately, is impossible to disentangle the actual time distribution among each leisure activity.

On a final note about the process of skill formation, returns on human capital investments can take time to realise, so most human capital investments are made in the first stages of life. We can only examine skill development if data is collected throughout different periods in time. Furthermore, recent evidence has also documented the fade out from early childhood interventions aiming to foster skills, though the analysis has focused mainly on developed economies (Bayley, Duncan, Odgers, & Winnie, 2017). We need comprehensive evidence analysing and identifying key features of child and adolescence interventions, as well as the characteristics and environments of their participants for mid-developing and developing countries. This will allow to document and identify characteristics that may explain persistence and fade-out of intervention effects over time, while providing valuable insights on the skill formation process.

Chapter 4 The role of birth order on children's time-use and parental educational aspirations: evidence from Peru

4.1 Introduction

There is an increasing interest to understand the dynamics and mechanisms along the life-cycle process of skill development and the intergenerational transmission of human capital. Past research documents that the family into which a child is born has a large impact on the course of her/his life. Cunha and Heckman (2007) developed a model on the technology of skill formation of human capital, documenting that child outcomes differences emerge from an early age (even before birth). Interest in the role of birth order driving different outcomes in children initiated from the findings of psychologists and sociologists (R.B. Zajonc, 1976; R.B. Zajonc & Markus, 1975). In the economics literature, the most popular explanations for the presence of birth order effects are resource constraints (e.g. income, access to credits, time spent at work versus home), household environments, biological effects, and cultural effects (Ejrnæs & Pörtner, 2004). One line of research sets parental investments or shifts on parental behaviour after observing the child's endowments as driver behind birth order and skill development differentials (Brenøe & Molitor, 2018; Ejrnæs & Pörtner, 2004; Lehmann, Nuevo-Chiquero, & Vidal-Fernandez, 2016; Pavan, 2016). Recent work by Molnár (2018) points to differential parental investment and differential time efficiency as important mechanisms behind widening skill gaps in early childhood.

In this chapter, I analyse the relationship of birth order with time use and parental educational aspirations for Peru. As highlighted in chapters 1 and 3, examining this topic within a context of high levels of inequality, is crucial to understand factors and mechanisms to help reduce inequalities early on. First, I examine the role of birth order as a key determinant of time use allocation, using extensive (school enrolment and child work binary outcomes) and intensive margins (time use outcomes). Following findings from previous investigations in developing contexts, my hypothesis is that the amount and the type of time-inputs allocation, will vary by birth order. In particular, I expect the oldest sibling will have allocated more time-inputs related to child work, and less so to time-inputs in leisure. For time-inputs in education, it might go to both directions (less or more), as this relationship is still empirically unclear. Second, I investigate if parental aspirations vary by birth order, one potential mechanism that might explain the child's time investments. This section will contribute to unpack the ambiguous relationship between birth order and the allocation of educational time-inputs, and add on the limited empirical literature examining the factors shaping parental aspirations. For this part, my hypothesis is that if parental aspirations do vary by birth order, e.g. if there are higher educational parental aspirations for the first-born sibling, this in turn will influence the child to allocate more time inputs in educational activities.

A major challenge in empirical studies into birth order is the endogeneity of fertility, which affects both family size and outcomes between children within the household. My empirical strategy restricts the sample to two-child families (only siblings born to the same mother) and relies on identification across households using a Correlated Randoms Effects model to overcoming the endogeneity of family size.[78] As emphasised in chapters 1 and 3, one motivation of the analysis in this chapter lies in the restricted literature on time use as an input for skill development and human capital transmission. Another motivation relates to improving our understanding of individual and household behaviour looking at time use of children and the role of parental aspirations in shaping time allocation.

For the first part on birth order differences, I find that higher birth order has a significant and negative effect on child work. In a two-sibling family and controlling for age, the second born child is 10.8 percentage points less likely to participate in child work; and spending 0.81 hours (about 49 minutes) less in care activities of other household members (e.g. younger siblings, elderly, or members with disabilities). The results on child work are robust to differences in family size, observed endowments (birthweight and cognitive score), and families with "complete" fertility decisions. I found no conclusive evidence of birth order effects for school participation, time spent in educational activities (school or studying), and time spent in leisure. The limitations due to sample restrictions are addressed in Section 4.4.

For the second part on parental aspirations, trying to unpack one possible channel driving the negative effect on child work time-inputs for second born siblings, I find parents are equally likely to aspire for the highest level of education, a University/Postgraduate degree, regardless to birth order. This finding holds for two and three children families. Furthermore, the negative effect in child work (i.e. time spent in care activities) for the second born, remains irrespective if parents aspire or not for their second born child to get a University/Postgraduate degree.[79] However, findings for this part are restricted due to data constrains discussed at length in Section 4.7.

My contribution is the following: first, unlike much previous work, I expand the analysis of time use beyond the school enrolment and child work participation indicators taking advantage of rich time use measures collected from Young Lives, an ongoing longitudinal household study in Peru and three other countries. Examining how individuals allocate their time outside of the market is vital for increasing our understanding of the dynamics of economic change and welfare (Gimenez-Nadal & Sevilla, 2012). I examine four different outcomes of daily time

[78]See Section 4.4 for a detailed explanation on the empirical strategy.
[79]Findings for this part are restricted due to data constrains discussed at length in Section 4.7.

distribution including hours spent at school, hours spent studying outside of school, hours spent on leisure activities, and hours spent on child work. The disaggregation of time use activities complements findings from chapter 3 and recent work efforts done by Keane, Krutikova and Neal (2018), Borga (2018), and Espinoza-Revollo and Porter (2018). Stiglitz, Sen and Fitoussi (2009) amid other academics have advocated in favour and proposed an array of measures of household economic activity to assess the quality of life, including time spent in leisure activities (Gimenez-Nadal & Sevilla, 2012). However, there is limited literature documenting any outcomes related to leisure activities for aged-school children. I also go beyond the standard definition of child work, following Morrow and Boyden (2018) and Espinoza-Revollo and Porter (2018), and look at disaggregated measures of child work, considering work within and outside the household and not exclusively for pay. Distinct from this previous work, I examine how the distribution of different types of work relates to the birth order position of the child within the family. Analysis of the production and domestic work within the children's homes is imperative for appropriate policy-making that reflects local circumstances (Morrow & Boyden, 2018). The present analysis also complements the limited literature on the link between parental aspirations and household (individual) resource allocation decisions. Dizon-Ross (2018) documents how parents tailor educational investments according to their (inaccurate) beliefs about their children's ability. Among the Young Lives countries, Morrow and Boyden (2018) document that Peru has the highest percentage of caregivers (81%) aspiring for their children to attend university; while Favara (2017) finds that for Ethiopia, being the oldest sibling decreases by 4.6 percentage points child's aspiration to attend University. Nonetheless, there is still limited literature on how aspirations shape decision making (O. Attanasio & Kaufmann, 2014; Chiapa, Garrido, & Prina, 2012).

The analysis of this chapter proceeds as follows. Section 4.2 goes through related literature on birth order and child's outcomes. Section 4.3 describes the data and outcomes. Section 4.4 discusses the empirical estimation strategy. Section 4.5 presents descriptive analysis and main results, while section 4.6 includes sensitivity analyses for family size, observed endowments and complete fertility decisions. Section 4.7 examines the relationship between birth order differences and parental aspirations; and finally, Section 4.8 concludes.

4.2 Related Literature

Most theories explaining intra-household resource allocation and relying on the resource dilution model[80], predict negative relationships between human capital development and

[80]The resource dilution model postulates that parental resources are finite and that as the number of children in the family increases, the resources accrued by any one child necessarily decline. Siblings

higher birth order (S. Black et al., 2005; Moshoeshoe, 2016). Empirically, the direction of birth order effects is still unclear given the mixed results, when looking at evidence from developed and developing countries. Findings from developed economies confirm better outcomes for firstborn children including more years of education, better achievement in cognitive tests, higher IQ, higher wages, and firstborn girls engaging in less risky behaviours (i.e. are less likely to give birth while teenagers) (S. Black, Devereux, & Salvanes, 2007; Lehmann et al., 2016; Pavan, 2016). For education outcomes, there are recurrent negative birth effects for younger siblings in developed countries (S. Black et al., 2005; de Hann, 2005; Grätz, 2018), but for developing countries evidence is varied. While Ejrnaes and Pörtner (2004), Emerson and Souza (2008), and de Hann, Pluge and Rosero (2014) find positive effects in completed years of education and/or educational achievement for Philippines, Brazil and Ecuador, Moshoeshoe (2016) find negative effects in enrolment and/or completed years of education for Lesoto for higher birth order siblings. On the inconsistency of birth order effects in education, he hints the divergence in findings are due to context-specific factors, related to the development of the country per se. On labour, studies using developing countries data and controlling for age, firmly document that higher birth order siblings are less likely to work, (Ejrnæs & Pörtner, 2004; Emerson & Souza, 2008; Moshoeshoe, 2016; Seid & Gurmu, 2015).

Outside the labour supply context, economists have overlooked the role of time use on skill acquisition and other well-being outcomes. Previous research on time use has investigated extensively the trade-off between education and child labour, mostly using binary outcomes of school enrolment and work participation (Cuesta, 2018; Ejrnæs & Pörtner, 2004; Emerson & Souza, 2008; Moshoeshoe, 2016; Seid & Gurmu, 2015). While investigating the trade-off between education and labour decisions is important, it offers an incomplete picture on how parents and children choose how to adjust resources across different margins, including time allocation among diverse activities. In his time allocation theory, Becker (1965) recognises that distribution and efficiency of non-working time might be more important to economic welfare than that of working time.

Driven by the parental investments channel, another narrow conceptualisation of time use surges when empirical analyses focus exclusively on the quantity, and sometimes quality of parental time (or parent-child interactions) (Del Bono et al., 2016; Molnár, 2018; Price, 2008). Beyond parental time, understanding the time use of children within the context of the household will improve our understanding of individual and household behaviour, along with the economic decision-making processes of households (Espinoza-Revollo & Porter, 2018). Likewise, own children's time distribution is informative of what is likely to matter for children's

are competitors for parents' time, energy, and financial resources and so the fewer the better (Downey, 2001).

wellbeing since where they spend their time will also determine the friends they make, the activities they take part in, and the risks they may be exposed to (Borga, 2018).

Most studies that find younger siblings are less involved in work rely on a narrow definition of what "work" includes. In all fairness, the choice of a "child labour" definition for empirical analysis is not straightforward (Edmonds, 2009). The debate has lasted for many years, led by the International Labour Organisation (ILO)[81], advocating for the elimination of child labour. One restriction of a child labour definition stems from these international regulations, where for many years, only working for pay and outside the household was classified as child work. It is not until very recently that working within or for their household is now considered as child work. The other restriction is due to data limitations. Using Peruvian (D. Levison & Moe, 1998) and Mexican (D. Levison, Moe, & Knaul, 2001) data, two analyses document that whether there is a trade-off between schooling attainment and work, depends on whether work includes domestic work, particularly for girls (Edmonds, 2009). In recent reports, Morrow and Boyden (2018) use descriptive information of children's working activities and qualitative experiences advocating for a more nuanced and comprehensive vision of child work for the four countries in the Young Lives study. Espinoza-Revollo and Porter (2018) offer a detail account of the evolving nature of time use during childhood and the influences that shape this process across the two Young Lives children cohorts[82]. Both reports fail to provide any causal explanation for child work (time use) and exclude birth order as explanatory factor for time-use trends.

Following latest research using Young Lives data (Cuesta, 2018; Espinoza-Revollo & Porter, 2018; Keane et al., 2018; Morrow & Boyden, 2018), I employ the term child work, instead of child labour. The difference between both terms is that child work considers work as "*part of children's everyday lives"* (Morrow & Boyden, pp. 5), recognising the daily life context of families from middle and low-income countries, where most children have always played a significant role in the production and domestic work within their homes (Morrow & Boyden, 2018). In short, the main difference is that it incorporates domestic work into the analysis of child work.

Finally, until which point child labour is harmful or beneficial for accumulation of human capital is an empirical question per se. There is a growing literature on the impact of child work on outcomes, providing important insights on its consequences. In education, Emerson, Ponczek, and Souza (2017) find that for girls, working while attending school translates into 5% and 13% decrease of a standard deviation in Mathematics and Portuguese test scores, respectively. The magnitude of the negative impact increases with student's ability; and, even

[81]ILO emits international regulations for governments to eliminate child labour. The main consensus thus far has been the definition of what is considered as hazardous work and the minimum age of engagement to work on these high-risk occupations.
[82]More information on the Young Lives data in Section 4.3 and chapter 1.

if the child is no longer working, lingering and cumulative negative effects on child's test scores persist from having worked while in school. Beegle, Dehejia and Gatti (2006) document child labour has negative consequences on school participation and educational attainment in Vietnam. Zabaleta (2011) examines the effect of child labour on distinct educational outcomes (years of education, grade for age, completion of primary education, and completion of at least a year of secondary education), finding a detrimental effect of working over three hours a day. Yet these studies are constrained to the standard (and narrow) definition of market work. In a more recent study, Keane, Krutikova, and Neal (2018) study trade-offs among time spent on the full vector of activities listed by Young Lives for accumulation of human capital. They find that both domestic chores and economic activities are detrimental to the development of cognitive skills if they crowd out school time. The detrimental effect of work time is even greater if it crowds out time spent studying at home. Finally, Espinoza-Revollo and Porter (2018) document that, for Peru, children of all ages in rural areas work significantly more than those in urban areas and that gender differences are not significant when considering the aggregate measure of work or education.

4.3 Data

As detailed in chapter 1, the data for this chapter's analysis comes from the Peruvian Younger Cohort of the Young Lives study. One specific aim of the sample restrictions for this chapter is maximise capturing school-age children, including not only the Young Lives child but also her/his siblings. With that end, I use data from the 2009 (Round 3) and 2012 (Round 4) survey rounds, comprising most of the school-aged children between 4-17 years old. Not until very recently, i.e. August 2018, Round 5 (2016) of data collection was made publicly available. However, at this later period, families with children where the Young Lives child has higher birth order, will be more likely to be dropped from the sample as the older sibling/s most likely has "aged out" the 17-years-old limit. Likewise, I exclude the earlier data collection periods, Round 1 (2002) and Round 2 (2006), as do not contain enough school-eligible children, particularly younger siblings from the Young Lives child. Although compulsory education in Peru starts at age three, data collection of time use is only for family members aged between four and 17 years old.[83]

Furthermore, I restrict the analysis to two children families (considering completed family size reported in Round 4) and only include siblings born to the same mother. The reasons for

[83]The General Education Law of 2003 establishes mandatory preschool education for ages three to five (before it was only for children aged five years old. The other compulsory levels of education include primary education (ages 6-11), secondary education (ages 12-14), *bachillerato academico* and *bachillerato tecnico* (ages 14-16).

this are twofold. First, to address endogeneity of fertility decisions (family size); and second, to attempt avoid including siblings with larger age differences between them. These and other methodological challenges are described in more detail in Section 4.4. Moreover, only families that were present in both rounds, and siblings with complete information of time-inputs and no missing information on a set of background measures including: main caregiver years of education, if child attended six or more months of preschool education, birth-space in years between siblings, child's language, household food expenditure, and wealth index, are included in the sample. After imposing the previous restrictions, the analytic sample for the study is set to 1336 children from 458 households observed in Round 3 and Round 4.[84]

4.3.1 Time use outcomes

The present analysis takes advantage of the fact that Young Lives collected time use information not only for the "Young Lives" child, but for all household members aged five[85] to 17 years old at the time of the survey. Information on time allocation is reported by main caregiver when child is between four and 11 years old, and by the child from 12 years onwards. It is plausible to argue that parents of school-age children can control more directly the time spent at school and studying, while at the same time, having more say in the type of child work children engage (Ejrnæs & Pörtner, 2004). As discussed in chapter 3, time use data is reported as number of hours the child spent on different activities on a typical weekday (Monday-Friday) in the last week. Regarding measurement error, some limitations of time use measures include having reported hours, not minutes; and data collected when school was in session, not capturing seasonality and possible underestimation of work done over the weekend (Espinoza-Revollo & Porter, 2018). However, even if these limitations translate into some noise of our time use outcome, is a lesser concern given its use as dependent variable, where at the most, the estimates' standard errors will increase, affecting precision.

As stated in Section 4.1, I investigate both extensive margins (school and child work participation indicators) and intensive margins (time use continuous outcomes). I construct the binary outcomes of school enrolment and child work participation with time data allocated to school and child work. For this, I use age normative cut-offs following official regulations from Peru's government (Ministry of Education) and the International Labour Organisation (ILO). A child is classified as enrolled (attending full-time education) or in child work according to the following age-ranges and quantity of time listed in Table 25.

[84] There are 12 problematic household ids that were excluded from the sample, related to the sibling's definition used (born to the same mother).
[85] Although official documentation from Young Lives establishes data collection of time use was for all household members starting age 5, for Peru the starting age was 4 years old.

Table 25. Description of binary indicators*

Outcome	Age range (years)	Weekly amount of time
School Enrolment[1]	4-5	▪ Child spent 16 or more weekly hours at school;
	6-11	▪ Child spent 30 or more weekly hours at school;
	12-17	▪ Child spent 35 or more weekly hours at school;
Child work participation[2]	4-11	▪ Child spent more than zero weekly hours working;
	12-14	▪ Child spent 14 or more weekly hours working;
	15-17	▪ Child spent 36 or more weekly hours working;

[1]A child was classified as enrolled (participating in FTE) based on age and weekly hours cut-offs from normative documents from UNESCO and the Ministry of Education in Peru (http://www.ibe.unesco.org/fileadmin/user_upload/Publications/WDE/2010/pdf-versions/Peru.pdf). For the ages 4-5 years old, 25 hours is the upper limit for preschool education offered in *Jardines*, a more institutional type of preschool. I used the lower bound of 16 hours a week, offered by *PRONOEI*, a public programme offering preschool education in marginal urban and rural areas (Cueto et al., 2016). [2]For child work participation, I used age specific cut-offs established by the International Labour Organisation (ILO). Young Lives collected data on what ILO considers light work and domestic work. The term light work is used to characterise the market work of children aged 12-14 in non-hazardous activities and for less than 14 hours per week. ILO Convention No. 138. stipulates that National laws or regulations may permit the employment or work of persons between 13 to 15 years old on light work that is unlikely to be harmful to their health and development; and not such as to prejudice their attendance at school, their participation in vocational or training programmes approved by the competent authority (e.g. Ministries of Education) or their capacity to benefit from the instruction received (Article 7, section 1). Peru's minimum age of commitment to engage in light work is 12 years old. Adolescents between 15 and 17 years may not work more than six hours a day, or over 36 hours a week (Article 56, Law 27337).

On the continuous outcomes, Young Lives collected time use information on eight different activities.[86] For simplification, in the main results I estimate the effect of birth order among four of the original eight activities asked in the household survey. I comprised child work related activities into one combined outcome.[87] The themes explored with the four time use outcomes can be split into education, recreational, and child work. The observed four outcomes are listed in Table 26.

Table 26. Description of Time-inputs*

Category		Outcome
Education	1	Number of hours per day the child spent at school (including travel time)
	2	Number of hours per day the child spent studying at home (including homework, extra classes, learning languages)
Recreational	3	Number of hours per day the child spent in leisure activities (playing, seeing friends, using the internet, eating, drinking, bathing etc.)
Child Work	4	(a) Number of hours per day the child spent in child-working activities such as caring for others (caring for younger children or sick household members); (b) Household chores (fetching water, cleaning, cooking, etc.); (c) Domestic tasks (farming, herding, etc); and/or (d) Working outside household on paid activities.

[86]To collect time-use data, 24 pebbles/seeds were offered to main caregivers and children which in turn have to distribute them into eight cups illustrating different activities. In Peru, the total time could range between 22 and 26 hours as interviewers allowed to count more than 24 hours if the child was doing different activities at the same time (e.g. household chores and caring for siblings/family members) (Espinoza-Revollo & Porter, 2018).
[87]As part of the complementary analysis and probing on child work estimates, I do investigate birth order effects for each of the child work outcomes.

*I am excluding from the analysis reported time spent sleeping. As a robustness test, I examine time use outcomes as percentage of the day spent in each activity to incorporate time spent sleeping in the analysis. These results are reported in Section 4.6. Information of time-use was collected for all children living in the household, which were between the ages four and 17. One restriction on the recreational time-inputs is that is not possible to disentangle the time spent in each individual activity defined as "leisure" in the questionnaire. The questionnaire only lists for the interviewer different examples of leisure activities spanning from playing to eating, while the latter might be better understood as routine/basic needs activity. An additional limitation is that time-spent at school includes transport, but I am controlling in the regression for cluster and location variables.

4.3.2 Other variables

The choice of explanatory variables is partly dictated by the availability of information in both rounds and the empirical model, described in Section 4. The time-invariant variables include: a female dummy indicator, binary indicators of child's language, ethnicity, and religion, a binary indicator of preschool attendance, a set of dummies indicating place of residence at birth, including region (Coast, Jungle, Mountain) and area (Urban/Rural); mother's age, main caregiver years of education; and age-difference among both siblings in years. The time variant controls include a household wealth index, a binary indicator of household cattle ownership in the past 12 months[88], household monthly expenditure in food items per capita[89], and a binary indicator if household head is female. Furthermore, I also include child's age dummies and cluster-village dummies, to control for year and village effects, respectively. Table 27 reports means and SDs for the main variables for the analytic sample, including mean comparisons against the Young Lives sample with all the family members aged four and 17 years-old (including all family sizes).

There are some small but significant differences between the two children families from the analytic sample and the Young Lives full sample. There are expected differences on birth order and number of siblings. More than 90% of the children in both samples has access to some preschool education. Mothers are around 2.7 years younger in the analytic sample than in the Young Lives sample. When baseline data collection took place (i.e. when the Young Lives child was between 0 and 2 years old), mothers were 24.5 years old, while for the Young Lives sample, they were 27 years old. Main caregiver in two child families are more educated. They have about 10 years of completed education (equivalent to completed secondary education and one year of high school), almost three years more than Young Lives sample. Furthermore, two children families are wealthier and had a higher food monthly expenditure, while the Young Lives sample had a higher percentage of families owning livestock in the past year (67% against 49%), which means a higher probability for children to potentially engage in herding.

[88]If the household owns cattle it might be expected to both increase the income of the household and reduce the cost of children as they could work in herding).
[89]Often used as a proxy for permanent income.

Table 27. Means and SDs (in parentheses) of analytic sample and Young Lives sample*

	Analytic Sample (I)	*Young Lives Sample* (II)	*Diff. in means* (III)
Child Characteristics			
Age (in years)	9.228 (2.843)	9.503 (3.142)	-0.275***
Birth order	1.449 (0.498)	2.716 (1.813)	-1.267***
Female (%)	0.504 (0.500)	0.499 (0.500)	0.005
Children attended preschool (%)	0.965 (0.184)	0.941 (0.236)	0.024***
Language is Spanish (%)	0.954 (0.209)	0.822 (0.383)	0.132***
Religion is Catholic (%)	0.839 (0.368)	0.807 (0.395)	0.032***
Other religion (%)	0.107 (0.309)	0.146 (0.353)	-0.039***
Ethnicity is Mestizo (%)	0.894 (0.307)	0.921 (0.269)	-0.027***
Ethnicity is White (%)	0.081 (0.273)	0.049 (0.216)	0.032***
Household Characteristics			
Number of siblings	2 (0.000)	4.047 (2.051)	-2.047***
Wealth index	0.647 (0.181)	0.538 (0.204)	0.109***
Household owned any livestock in the past 12 months	0.492 (0.500)	0.674 (0.469)	-0.182***
Monthly expenditure in food items per capita	154.105 (79.594)	117.679 (66.173)	36.426***
Parental Characteristics			
Mom age (at birth)	24.463 (5.471)	27.030 (6.464)	-2.567***
Caregiver years of education (at birth)	9.912 (3.865)	7.088 (4.578)	2.824***
Head of household is female (%)	0.167 (0.373)	0.127 (0.333)	0.040***
Region Characteristics			
Child lives in Coast region (%)	0.451 (0.498)	0.301 (0.459)	0.150***
Child lives in Mountain region (%)	0.412 (0.492)	0.548 (0.498)	-0.136***
Child lives in Jungle region (%)	0.138 (0.345)	0.151 (0.358)	-0.013***
Child lives in Urban area (%)	0.821 (0.383)	0.623 (0.485)	0.198***
Child lives in Rural area (%)	0.179 (0.383)	0.377 (0.485)	-0.198***
Observations (Children)	1336	7409	

[3]Column I includes analytic sample restrictions described in 3.1. Column II includes YL sample, restricted to households observed in Round 3 and Round 4 and children aged 4-17 years old. Column III reports differences in means from Column I and Column II, where: ***p<0.001, **p<0.01, *p<0.1 Other religion category includes Evangelic, Mormon and Hindu. [4]The wealth index is a composite measure of three sub-indexes: a housing quality index, access to services index, and consumer durables index. The three sub-indexes were estimated consistently across rounds and only variables common to the four available rounds at that moment were included. The housing quality sub-index is the average of the following dummy indicators: crowding, main material of walls, main material

of rood, and main material of floor; the access to services sub-index is the averaged of the following dummy indicators: access to electricity, access to safe drinking water, access to sanitation, and access to adequate fuels for cooking: the consumer durables index is the average of a set of dummy variables denoting if a household member owns at least one of each consumer durable. The list of consumer durables included: radio, television, bicycle, motorbike, automobile, landline phone, mobile phone, refrigerators, stove, blender, iron, and record player.
[5]Food expenditure per capita expressed in real terms of the national currency (*Soles*) adjusted for local inflation and for household size across time. More details on the wealth index and food expenditure can be found here (Azubuike & Briones, 2016) and here (Marion, 2018), respectively.

4.4 Empirical Estimation

An empirical analysis of birth order differences is complex given the endogeneity of fertility, with unobserved preferences affecting both family size and outcomes of children within the household.

To overcome the endogeneity of family size, my empirical strategy restricts the sample to two-child families (only siblings born to the same mother) and relies on identification across households. Families who choose to have different numbers of children are likely to be fundamentally different both in observed and unobserved characteristics. Whilst we can control for the former, we cannot control for unobserved differences – however, restricting the analysis for two children families removes must of the confounding due to family size differences (and improves higher likelihood of homogeneity in family unobserved characteristics), I estimate birth order effects with a Random Effects[90] (RE) model, denoted in Eq (1):

$$\gamma_{ift} = \theta_t + \beta_j(Birth\ order_{if} = j) + \varphi x_{ift} + \alpha z_{ft} + (\mu_f + \varepsilon_{ift}) \qquad (1)$$

where i indexes the child, f indexes the family, t indexes the time period, and j indicates the birth order of the child ($j = 1, 2$). Y_{ift} is the dependant variable (i.e., school and child work binary indicators or time use continuous variables); θ_t denotes a time-varying intercept; β_j is the parameter of interest, capturing differences for being the second born ($j = 2$) with respect to the first born ($j = 1$) omitted category; x_{ift} denotes a vector of time-variant and invariant child characteristics that affect Y_{ift}, including age of the child, birth space between siblings, child's language, child's ethnicity, child's religion, if child attended preschool, and child's sex, all defined as dummies; z_{ft} is a vector of time-variant and time-invariant family characteristics, including a household wealth index, an indicator of household cattle ownership, household monthly expenditure in food per capita, mother's age, main caregiver years of education, a

[90]Also called multilevel models, hierarchical linear models and mixed models (Bell & Jones, 2015; Rabe-Hesketh & Skrondal, 2012; Schunck & Perales, 2017). Eq (1) also assumes that μ_f and ε_{ift} are normally distributed, and hence, an overall measure of the respective variances can be estimated as: $\mu_f \sim N(0, \sigma_\mu^2)$ and $\varepsilon_{ift} \sim N(0, \sigma_\varepsilon^2)$. Regardless, even when the Normality assumptions are violated, RE models perform well (Bell & Jones, 2015).

dummy for sex of household head, and dummies denoting family place of residence[91]; μ_f is the family level residual constant across time, while ε_{ift} is the idiosyncratic error term that varies across children and time (hereafter consider as white noise). The μ_f term is in effect a measure of "similarity", which allows for dependence as is related to all family level repeated measures (Bell & Jones, 2015).

Eq (1) assumes two children families share the same observed and unobserved characteristics ($Cov(x_{ift}, \mu_f) = 0$), and extends that assumption to child-level characteristics and their residuals ($Cov(x_{ift}, \varepsilon_{ift}) = 0$)[92]. However, there still might be (un)observed heterogeneity within two children families even if they are more similar than single child or high birth order families. After conducting a set of relevant tests[93], I relax the assumption of $Cov(x_{ift}, \mu_f) = 0$, and replace it with $\mu_f = \pi\bar{x}_f + v_f$, resulting in a correlated random effects (CRE) model as shown in Eq (2) below[94]:

$$\gamma_{ift} = \theta_t + \beta_j(Birth\ order_{if} = j) + \varphi x_{ift} + \alpha z_{ft} + \pi\bar{x}_f + v_f + \varepsilon_{ift} \quad (2)$$

where $\bar{x}_f$, the cluster mean of x_{ift}, picks up any correlation between this variable and the family level error v_f. The family-level characteristics included in $\bar{x}_f$ are the household wealth index, the household cattle ownership indicator, household monthly expenditure in food per capita and sex of household head[95]. Each estimation is clustered at the family level, to account for the variation that occurs at this level and any time-invariant variables, including $Birth\ order_{if}$. Introducing $\mu_f = \pi\bar{x}_f + v_f$ in Eq (2), allows to both account for (and include) family-level factors that are correlated with birth order and child outcomes, and consistent estimation of

[91]The list of family location covariates includes dummies for region (Coast, Mountain, or Jungle) and area (Urban or Rural) where family lived at baseline, and time-variant dummies for villages.

[92]Known in the literature as the exogeneity assumption of Random Effects models.

[93]A Durbin-Wu-Hausman Test after a second stage regression on $\widetilde{birth\ order_{if}}$ residuals shows RE (Eq 1) is not consistent (DWH $X^2\,(1) = 3.05$, *p-value* = 0.081). Furthermore, results from a Wald test conducted to compare the RE (Eq 1) model against the CRE (Eq 2) model, shows the CRE model fits the data better (Wald $X^2\,(69) = 34322.11$, *p-value* = 0.000); and results on the zero correlation assumption ($\pi = 0$) from Eq (2), show the null hypothesis is rejected, join test (Wald $X^2\,(4) = 1.73$, *p-value* = 0.786). These results are also considered as evidence supporting the use of CRE against the RE model (Schunck, 2013; Wooldridge, 2010).

[94]For clarification, I estimate two CRE probit models for the binary indicators. When looking at both binary outcomes (school and child work participation), previous studies have used a bivariate probit model, assuming parents jointly allocate the child's time between those activities (Emerson & Souza, 2008; Seid & Gurmu, 2015). The bivariate probit model is used where a dichotomous indicator is the outcome of interest and the determinants of the probable outcome includes qualitative information in the form of a dummy variable where, even after controlling for a set of covariates, the possibility that the dummy explanatory variable is endogenous cannot be ruled out a priori (Chuhui, Poskitt, & Zhao, 2016; Seid & Gurmu, 2015). I ran bivariate probit models as robustness check, results are quite similar from separate probit models and listed in Table C4 in the Appendix.

[95]In practice, $\bar{x}_f$ is only calculated for time-variant covariates. Time effects, age and round, are excluded from the cluster mean calculation as their averages will be all the same and they are collinear with the regression constant. See Table C1 in the Appendix showing the within and between variation of the variables among both rounds.

level-one (child) effects, including time-invariant predictors (Mundlak, 1978; Schunck, 2013; Wooldridge, 2010). An advantage of the CRE approach is the possibility to make simple, robust tests of correlation between heterogeneity and covariates (effectively, testing $\pi = 0$) (Bell & Jones, 2015; Schunck & Perales, 2017).

Other well-known methods to account for (un)observed heterogeneity within families and endogeneity in family size are family Fixed Effects (FE) and Instrumental Variables (IV). Debate between disciplines against or in favour between FE and RE is extensively covered elsewhere (Bell & Jones, 2015; Elzinga & Gasperini, 2015; Wooldridge, 2010). A prime motivation for using a RE model is that it allows to examine relationships between the characteristics of the family-level unit and the child-level outcome of interest including family-level covariates (Clarke, Crawford, Steele, & Vignoles, 2010). Furthermore, I cannot estimate a family FE model as my coefficient of interest, β_j, does not vary across time and within family (given I am using observed birth order in last round available). Family size is also invariant, as I am focusing on two children families for the main analysis. On IV, twin births and siblings sex composition are two widely instruments employed on this literature. Due to data restrictions, finding a valid exogenous instrument seemed unfeasible plus any argument in favour of the chosen IV is always debatable (e.g. arguing country and cultural preferences for boys over girls) and would increase the likelihood of incurring in Type II error.

Finally, whilst the identification strategy is cleaner by comparing birth order effects within siblings and between families of the same parity, it reduces the representativeness of the sample, with a cost upon the external validity of the results. Likewise, a key issue from Eq (2) is to estimate an unbiased coefficient of $Birth\ order_{if}$. This is done by controlling for a rich list of child-level characteristics that are associated with children being the second born child and with the outcome of interest, denoted in x_{ift}. Regardless, a set of sensitivity checks to probe the estimates are conducted in Section 4.6.

4.5 Results

This section enlists and discusses the main results derived from estimating Eq (2) for the binary and continuous time use outcomes, by pooling together the complete analytic sample and controlling for the full vector of child[96] and family characteristics denoted in Section 4.4.

[96]Including age and gender, so the birth order estimate is not confounded by these effects. In Section 4.6, one sensitivity analysis includes restricting the sample to same sex families.

4.5.1 School enrolment and work participation

Table 28 below shows the percentage distributions for the school enrolment and child work indicators for the analytic sample when children were 7-8 years old. There are no differences regarding school enrolment as about 80% of first and second born children are enrolled at school around those ages. There is a higher percentage of first-born children involved in child-work (75%) with respect to their younger sibling (68%) when both reached the same age range.

Table 28. Percentage distribution for school attendance and child-work participation (by ages 7-8)

		First born (j =1)	Second born (j =2)	Diff. in means
School enrolment	**(%)**	0.814	0.804	0.009
Child-work participation	**(%)**	0.745	0.684	0.060
Observations			1336	

*Own calculation using time use data normative cut-offs by age for full-time enrolment (if at ages 4-5 years old was spending 16 or more weekly hours at school, if at ages 6-11 years old was spending 30 or more weekly hours, and if at ages 12-17 years old was spending 35 or more weekly hours) and child work participation (if at ages 4-5 years old was involved in any child work activity for one or more weekly hours, if at ages 12-14 was working 14 or more weekly hours, and if at ages 15-17 was working 36 or more weekly hours).

Examining this relationship under Eq (2), Table 29 presents the Average Marginal Effects (AMEs) for the CRE probit models for school and child work participation. Results indicate that, being the second born decreases the probability of child work by 10.7 percentage points in a two-child family (significant at less than 1% level). The finding is consistent with previous results using developing countries data (Emerson & Souza, 2008; Moshoeshoe, 2016; Seid & Gurmu, 2015). The result on school enrolment for birth order is also negative but smaller in magnitude and not statistically significant. This finding is aligned with Ethiopia (Seid & Gurmu, 2015) and Lesoto (Moshoeshoe, 2016), but opposed to evidence from Philippines (Ejrnæs & Pörtner, 2004) and Brazil (Emerson & Souza, 2008).

An interesting finding for school enrolment is the negative relationship between this outcome and age. As child gets older, it decreases the probability of school enrolment.[97] This finding concurs with the transition to upper secondary in Peru by age 14, suggesting children leave school when reaching that grade (Espinoza-Revollo & Porter, 2018). For child work, the negative birth order effect is similar in magnitude whether if the household head is female, decreasing the probability of engaging in child work by 10.8 percentage points.[98] AMEs for other variables and results from the bivariate probit model, which is similar to main results here

[97]About 67 percentage points less by age 16, significant at less than 1% level.
[98]Significant at the 1% level.

(-0.091, significant at the 5% level), are reported in Table C3 and Table C4, respectively, in the Appendix.

Table 29. Average Marginal Effects: school enrolment and child work

	School enrolment (I)	*Child work participation* (II)
AME: Birth order (j =2)	-0.023	-0.103**
	(0.031)	(0.033)
p-value $H_0: \beta_1 = \beta_2 = 0$	0.393	0.002
Observations	1324	1253

***p<0.001, **p<0.01, *p<0.05. Standard errors in parentheses. Each column presents a separate regression. All regressions include controls reported in Table C3 in the Appendix. For child work participation, age 4 observations are dropped from estimation as this category predicts failure perfectly. Testing the null hypothesis for zero correlation between heterogeneity and covariates ($\pi = 0$), gives a *p-value* of 0.297 (Column I) and a *p-value* of 0.708 (Column II).

4.5.2 Time use in education, leisure, and work

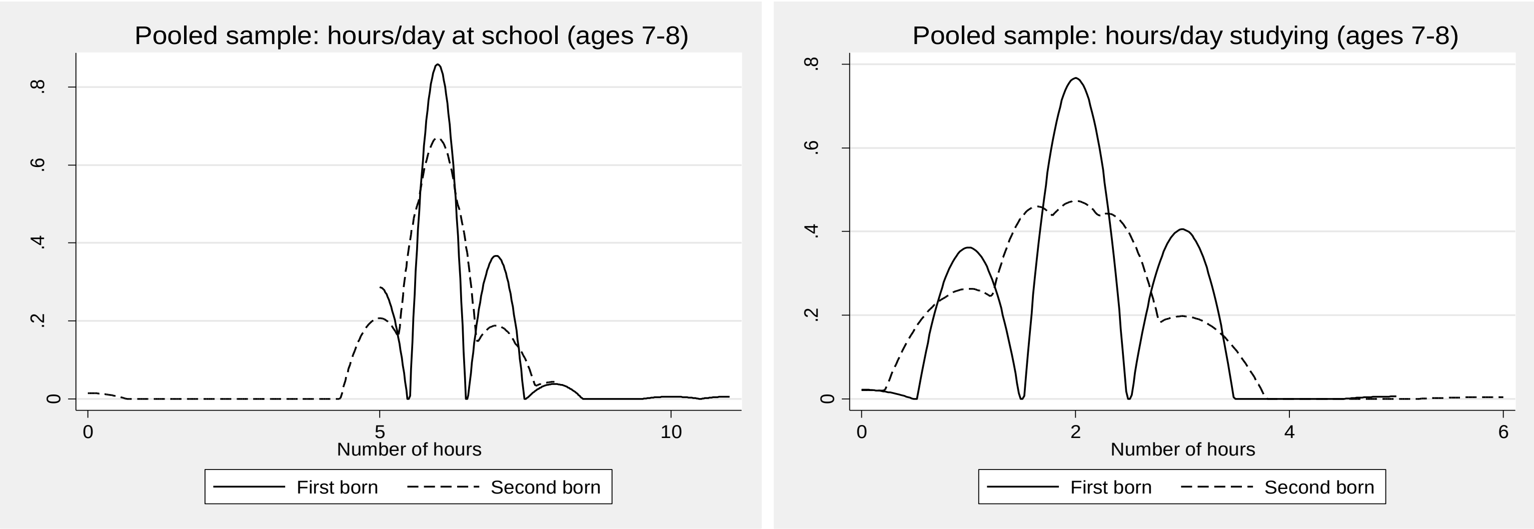
Table 30 reports means and difference in means of time use, when both children were the same age (between 7-8 years old), while Figures 5a and 5b display Kernel density estimates of time use for first and second born children using the analytic sample. There are no sizeable differences between first and second born children in time use for educational activities. In contrast, results show that second born child consistently spends less time in child-work activities (0.62 hrs/37 min) and more time in leisure activities (0.46 hrs/28 min), and both differences are statistically significant at the 1% level. Figure 4b displays a highly left-skewed distribution on time use related to child work (most of the sample of children work between zero and less than two hours).

Table 30. Means and difference in means of time use by analytic sample

	Hrs/day at school			*Hrs/day studying outside school*			*Hrs/day in leisure*			*Hrs/day in child-work*		
	First born (*j* =1)	Second born (*j* =2)	Diff. in means	First born (*j* =1)	Second born (*j* =2)	Diff. in means	First born (*j* =1)	Second born (*j* =2)	Diff. in means	First born (*j* =1)	Second born (*j* =2)	Diff. in means
	(Ia)	*(Ib)*	*(Ic)*	*(IIa)*	*(IIb)*	*(IIc)*	*(IIIa)*	*(IIIb)*	*(IIIc)*	*(IVa)*	*(IVb)*	*(IVc)*
2 siblings	6.128	5.987	0.141	2.017	1.898	0.119	3.969	4.427	-0.458**	1.638	1.018	0.620***
Observations (children)							1336					

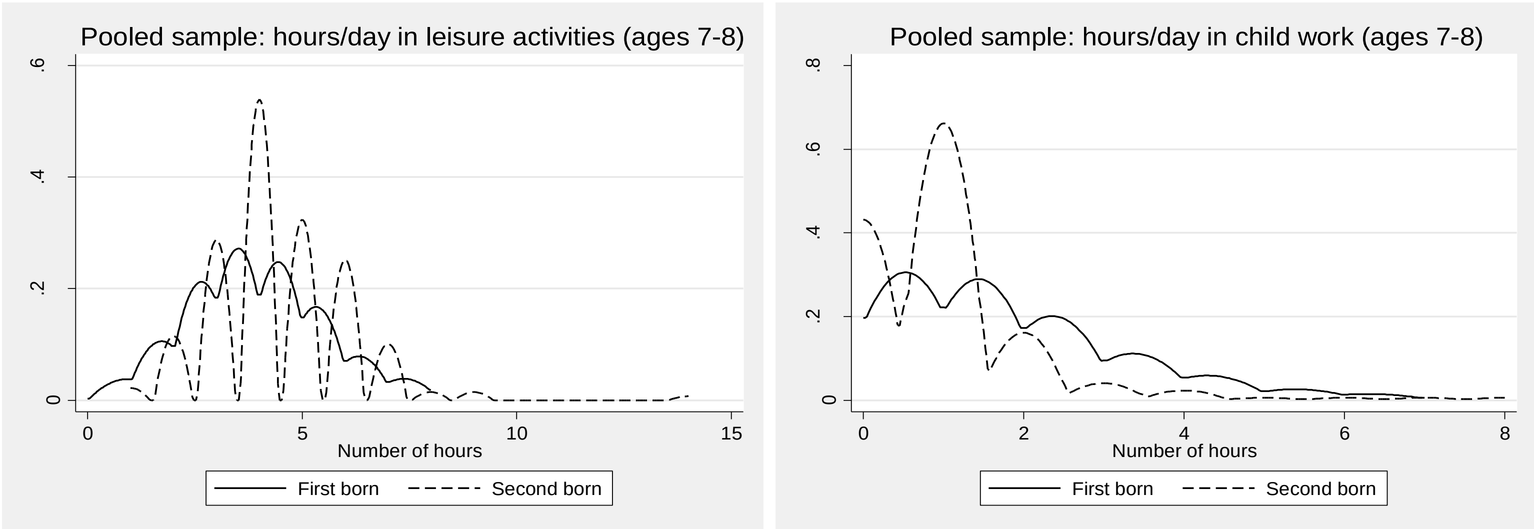
***p<0.001, **p<0.01, *p<0.05. All estimates include sample restrictions (listed in Section 3). Outcomes of time-use are winsorized (trimmed) at the 95th percentile.

Figure 5a. Distribution of hours spent at school and studying by birth order (ages 7-8 years old)



*Kernel density graphs of time-use outcomes for first and second born children when both were between 7-8 years old. Outcomes of time-use are winsorized (trimmed) at the 95th percentile.

Figure 5b. Distribution of hours spent in leisure and child work by birth order (ages 7-8 years old)



*Kernel density graphs of time-use outcomes for first and second born children when both were between 7-8 years old. Outcomes of time-use are winsorized (trimmed) at the 95th percentile.

Tables 31a and 31b present the estimation results for the CRE model (Eq 2). Point estimates in Table 31a imply that time spent at school and in child work activities (aggregate) decreases with birth order, while it increases for time spent in leisure. However, only coefficients of birth order for child work and leisure are statistically significant (Columns III and IV). Specifically, being the second born child decreases the quantity of time spent in child work by 0.81 hrs (48 min) and increases the amount of time spent in leisure activities by 0.33 hours (20 min), contrary to the first born. See Table C5 in the Appendix for the coefficients on the rest of the variables.[99]

However, the test on the null hypothesis that the coefficients of the cluster-means are jointly equal to zero ($\pi = 0$), is rejected (at the 5% level) for the estimates of hours spent at school (Column I) and hours spent in leisure (Column III). It means that for both outcomes the CRE birth order estimate is inconsistent, i.e. there are time-invariant unobservables related to the outcome[100]; and only the coefficients for time spent in child work and time spent studying outside school, are valid and consistently estimated under CRE assumptions. To correct for this, I employ the Hausman-Taylor (HT) estimator to control for heterogeneity differences in families (due to the rejection of the zero-correlation hypothesis) for Columns I and III outcomes. Hausman and Taylor (1981) developed an IV estimator based on the random-effects transformation, allowing to obtain consistent estimation for the endogenous time-invariant regressor. It makes the stronger assumption that some specified regressors are uncorrelated with the fixed effect (Cameron & Trivedi, 2009). Results from HT estimation are qualitatively similar to the main results[101] and listed in Table C12 in the Appendix.

Table 31a. CRE estimates

	Hrs/day at school (I)	*Hrs/day studying outside school* (II)	*Hrs/day in leisure* (III)	*Hrs/day in child-work* (IV)
Birth order (j =2)	-0.120	0.071	0.328**	-0.813***
	(0.071)	(0.062)	(0.118)	(0.104)
p-value $H_0: \beta_1 = \beta_2 = 0$	0.092	0.251	0.005	0.000
R-squared	0.293	0.207	0.260	0.360

[99]Regarding the other predictors, there is a positive relationship between age and hours spent in child work, increasing while the child gets older and reaching up to 2.9 hrs by age 17. Another important variable is the child-spacing between siblings. The amount of time spent in child work modestly decreases while the gap in years among both siblings gets larger. The first substantial decrease comes when the birth spacing goes from seven (-0.45 hrs) to eight years (-0.73 hrs). There is a small but significant (at the 5% level) gender difference in the quantity of hours spent in child work. If the child is a girl, she spends 0.141 hrs (9 minutes) more in child work activities per day.

[100]For time spent at school, the variable that stands out is the family cluster-mean for wealth index (1.536***). It means one unit increase in the family wealth index translates to an increase of 1.5 hours spent at school. For time spent in leisure, the distinct coefficient corresponds to the family cluster-mean of food expenditure is (-0.004*).

[101]The coefficient for hours spent at school (Column I) change sign from negative to positive (from -0.120 to 0.251 hrs) and for hours spent in leisure (Column III) it decreases (from 0.328 to 0.153 hrs), with respect to the CRE main results. None of them are statistically significant.

	Hrs/day at school (I)	Hrs/day studying outside school (II)	Hrs/day in leisure (III)	Hrs/day in child-work (IV)
Observations	1336	1336	1336	1336

***p<0.001, **p<0.01, *p<0.05. Clustered robust standard errors at the family level in parentheses. Each column presents a separate regression. All regressions include controls reported in Table C5 in the Appendix. Testing the null hypothesis for zero correlation between heterogeneity and covariates ($\pi = 0$), gives the following *p-values:* 0.000 (Column I), 0.085 (Column II), 0.022 (Column III), and 0.360 (Column IV). See Table C12 in the Appendix for Hausman-Taylor estimates for Columns I and III.

Disaggregating each of the child work activities (Table 31b) reveals a key insight into the type of child work Peruvian children spent more (less) by birth order. As mentioned before, most children are not involved in paid work outside the household. We find that the negative effect of birth order for child work is driven by time spent in caring activities. The second born child spends 0.81 hrs (49 min) less per day in care activities than the firstborn sibling. The effect is larger than any of the other determinants in the model, regardless of the age of the child and birth-spacing among siblings.[102] There are no significant gender differences in the division of labour, only to mention that girls spent more time in household chores than boys, about 0.094 hrs more.[103] The zero-correlation assumption at the family level ($\pi = 0$) holds for all regressions. Coefficients for the rest of the predictors for Table 31b are listed in Table C6 in the Appendix.

Table 31b. CRE estimates: child work disaggregated

	Hrs/day care (V)	Hrs/day chores (VI)	Hrs/day household tasks (VII)	Hrs/day paid work (VIII)
Birth order (j =2)	-0.808***	0.024	0.003	-0.001
	(0.054)	(0.048)	(0.055)	(0.024)
p-value $H_0: \beta_1 = \beta_2 = 0$	0.000	0.608	0.957	0.963
R-squared	0.313	0.233	0.172	0.080
Observations	1336	1336	1336	1336

***p<0.001, **p<0.01, *p<0.05. Clustered robust standard errors at the family level in parentheses. Each column presents a separate regression. All regressions include controls (not reported in table) reported in Table C6 in the Appendix. Testing the null hypothesis for zero correlation between heterogeneity and covariates ($\pi = 0$), gives the following *p-values:* 0.800 (Column V), 0.579 (Column VI), 0.744 (Column VII), and 0.390 (Column VIII).

In sum, results from this section suggest the negative effect for the second born sibling in child work, related to time spent in caring activities is substantial, especially compared to the rest of the predictors for time use. This result is in line with previous empirical evidence using middle and low-income country data (Ejrnæs & Pörtner, 2004; Emerson & Souza, 2008;

[102]In fact, only for ages seven (-0.151 hrs), 10 (-0.285 hrs), and 11 (0.374 hrs), coefficients are significant at the 1% level but still smaller than the birth order effect. The same applies for birth-spacing, as only when the space gap between siblings is 10 (-0.305 hrs) and 15 (-0.224 hrs) years, coefficients are significant at the 1% and 5% level, respectively.
[103]Girls spent more time in hours related to care (0.038 hrs), while boys spent more time in paid work (0.021 hrs), but none of the coefficients are statistically significant.

Moshoeshoe, 2016; Seid & Gurmu, 2015), where findings point to negative effects between children of higher birth order and child work.

In contrast, findings are unclear for time spent in education. The birth order effect of hours spent at school goes from negative to positive after the Hausman-Taylor correction although coefficients in both methods are not significant. A similar pattern is observed in Seid and Gurmu (2015) when addressing endogeneity of family size by IV estimation[104]; while the Correlated Random Effects estimate for hours spent studying outside school is positive and also not significant. These results relate to the mixed evidence of birth order effects in developing countries for educational outcomes (de Hann, Pluge, & Rosero, 2014; Ejrnæs & Pörtner, 2004; Emerson & Souza, 2008; Moshoeshoe, 2016).

Finally, on leisure results, the adjustment after HT led to a decrease in the birth order coefficient for the second born child, from 0.328 hrs to 0.153 hrs and resulting in no longer being statistically significant.

4.6. Sensitivity analysis

To address concerns of omitted variable bias, external validity, an further endogeneity in family size[105], I conduct three different sensitivity checks, re-estimating Eq (2) by: (1) adding birthweight and a cognitive score to proxy for child's ability (mild sample restriction); (2) restricting the analytic sample to children with "older" mothers, who are less likely to still be making fertility decisions and adding birthweight (strongest sample restriction)[106]; and (3) comparing same-sex two children families with three children families (weaker sample restriction). [107]

[104]Their school enrolment average marginal effect is negative and insignificant in models not controlling for endogeneity of family size (-0.002) and becomes positive in their preferred bivariate probit IV specification (0.014), but still insignificant.

[105]Emerson and Souza (2008) argue that the family size variable can be endogenous for two main reasons. First, it could be that it is correlated with the error term because it is measuring two different things, completed fertility for some families, and current children for families that have not yet finished having kid. The second way fertility might be correlated with the error term is because investment in children and number of children could be jointly determined.

[106]Mother's mean age for the analytic sample is 24 years old (at baseline). In this restriction, I use the mean age observed in the 75 percentiles, 28 years old (at baseline). Naturally, sample size for this check, also including birthweight, is considerably smaller (N = 265) from the main analytic sample (N = 1336).

[107]The mean number of children in the unrestricted sample of Young Lives children is 4.3. However, the total fertility rate for Peru, following the global fertility trend, has been decreasing in the past 50 years and in 2016 it was 2.4 births per women (The World Bank, 2018). Hence, using two-children families for the main results offers a closer account of the current family composition in Peru.

4.6.1 Less restricted sample: Family size

To test for heterogeneity in the effect of birth order by family size, I estimate all CRE regressions for the time-use continuous outcomes separately by different family sizes with same-sex children (e.g. two boys, two girls, three boys, three girls).[108] Table 32a below compares estimates between families with two children (Columns Ia-IVa) and three children (Columns Ib-IVb). When comparing the estimates with three children families, the birth order coefficient for the third born is equivalent to the second born child in two sibling families (in magnitude and statistical significance). On average, being the second born sibling in a two-child family and the third born sibling in three children families decreases the daily number of hours spent caring for any other household member by 0.787 hrs (47 min), whilst the second born in three child families spends 0.348 hrs (21 min) less, in contrast of their firstborn sibling. For two children families, the negative effect of time spent in child work for the second born child remains significant, though restricting the analysis to same-sex siblings reduces the magnitude of the coefficient by 0.133 hrs with respect to the main results in Table 31a (going from -0.813 to -0.682 hrs).

Including three child families in the analysis brings more informative results for time spent in leisure. The second and third born child spend more hours in leisure activities, up to 0.276 hrs (17 min) and 0.534 hrs (32 min) more than the oldest sibling. Results for all coefficients are included in Table C7 in the Appendix.[109]

When decomposing child work in Table 32b, the birth order coefficient for hours spent in care activities is negative, significant (at less than 1% level), and same in magnitude for the second born in two sibling families and for the third born in three child families, amounting to -0.787 hrs (47 min). There is also a negative effect for the second born in three child families but smaller than for the third born (-0.348 hrs/21 min). Surprisingly, there is a small positive birth order effect for the second and third born in three child families for daily hours worked in paid activities. The result of 0.154 hrs (9 min) is only significant for the second born child (at the 5% level). See Table C8 in the Appendix for the complete list of coefficients.[110]

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[108] I also examined birth order differences for four children families. However, sample size decreases dramatically (only 426 children-data points observations), as there are not enough same-sex four children families, and inference is invalid (standard errors increase). For four siblings, the negative birth order effect in child work for the fourth child is smaller in magnitude (in contrast with two and three child families), and positive for the second and third born, but none of the coefficients are statistically significant. Results are available upon request.

[109] There is a clear inverse relationship for both two, and three sibling families, between age and the amount of time in leisure. Values range from -0.597 hrs (36 min) to -0.961 hrs (58 min) at age five, and from -2.100 hrs (126 min) to -2.741 hrs (165 min) by age 17, respectively. In families with three siblings if child ethnicity is White, it means a 1.093 hr increase in leisure activities.

[110] On the rest of the predictors, it seems the birth order effect is driven by siblings aged 15 years old and older, as it is when the first substantial increase is observed. Youngsters aged 15, 16, and 17 spend between 0.884 and 2.70 hrs more in paid work. There are larger gender differences (still small in

As in the main results, the zero-correlation hypothesis ($\pi = 0$) that estimation by CRE is consistent, i.e. no correlation between heterogeneity and covariates, fails for hours spent at school (Columns Ia and Ib) and hours spent in child work (Column IVb). Hausman-Taylor estimates are reported in Table C13 in the Appendix.[111]

magnitude) in the division of labour for same-sex families, in contrast with the main results from Table 31b (coefficients found in Table C6). In two children families, girls spent more time in hours related to care (0.098 hrs/6 min), while boys spent more time in paid work in both two (0.047 hrs/3 min) and three (0.109 hrs/7 min) sibling families. These results are aligned with Crivello and Espinoza-Revollo (2018).

[111]HT results show the coefficients for hours spent at school switch sign for Column Ia (from -0.136 to 0.782) and for the second born in Column Ib (from -0.092 to 0.099); while increasing for the third born child in Column Ib (from -0.151 to -0.891). For hours spent in child work (Column IVb), coefficient for the second born increases (from -0.150 hrs to -0.409 hrs), whilst decreasing for the third born and is no longer statistically significant (from -0.681 hrs to -0.594 hrs).

Table 32a. Sensitivity CRE: By Family Size

	2 siblings				3 siblings			
	Hrs/day at school	*Hrs/day studying outside school*	*Hrs/day in leisure*	*Hrs/day in child-work*	*Hrs/day at school*	*Hrs/day studying outside school*	*Hrs/day in leisure*	*Hrs/day in child-work*
	(Ia)	(IIa)	(IIIa)	(IVa)	(Ib)	(IIb)	(IIIb)	(IVb)
Birth order (j =2)	-0.136 (0.091)	0.082 (0.076)	0.280 (0.151)	-0.682*** (0.128)	-0.092 (0.086)	-0.017 (0.065)	0.276* (0.115)	-0.150 (0.136)
Birth order (j =3)					-0.151 (0.139)	-0.084 (0.099)	0.534** (0.189)	-0.681*** (0.173)
p-value $H_0: \beta_1 = \beta_2 = 0 \mid \beta_1 = \beta_2 = \beta_3 = 0$	0.132	0.28	0.063	0.000	0.496	0.603	0.015	0.000
R-squared	0.301	0.209	0.272	0.367	0.350	0.226	0.301	0.413
Observations	1076	1076	1076	1076	1035	1035	1035	1035

***p<0.001, **p<0.01, *p<0.05. Clustered robust standard errors at the family level in parentheses. Each column presents a separate regression. All regressions include controls reported in Table C7 in the Appendix. Columns Ia-IVa correspond to two sibling families, excluding 12 households where the sibling definition confounds the true family size. Columns Ib-IVb correspond to three sibling families, excluding 17 problematic household ids and 2 households with twins. Testing the null hypothesis of zero correlation between heterogeneity and covariates ($\pi = 0$), gives the following *p-values:* 0.000 (Column Ia), 0.231 (Column IIa), 0.292 (Column IIIa), 0.590 (Column IVa), 0.060 (Column Ib), 0.354 (Column IIb), 0.705 (Column IIIb), and 0.001 (Column IVb).

Table 32b. Sensitivity CRE: By Family Size (child-work disaggregated)

	2 siblings				3 siblings			
	Hrs/day care	*Hrs/day chores*	*Hrs/day household tasks*	*Hrs/day paid work*	*Hrs/day care*	*Hrs/day chores*	*Hrs/day household tasks*	*Hrs/day paid work*
	(Va)	(VIa)	(VIIa)	(VIIIa)	(Vb)	(VIb)	(VIIb)	(VIIIb)
Birth order (j =2)	-0.787*** (0.062)	0.028 (0.055)	0.070 (0.071)	0.011 (0.039)	-0.348*** (0.075)	0.021 (0.051)	0.039 (0.059)	0.154* (0.076)
Birth order (j =3)					-0.789*** (0.090)	-0.061 (0.070)	0.049 (0.090)	0.147 (0.075)
p-value $H_0: \beta_1 = \beta_2 = 0 \mid \beta_1 = \beta_2 = \beta_3 = 0$	0.000	0.607	0.324	0.784	0.000	0.239	0.805	0.118
R-squared	0.327	0.253	0.180	0.094	0.256	0.304	0.278	0.220
Observations	1076	1076	1076	1076	1035	1035	1035	1035

***p<0.001, **p<0.01, *p<0.05. Clustered robust standard errors at the family level in parentheses. Each column presents a separate regression. All regressions include controls reported in Table C8 in the Appendix. Columns Ia-IVa correspond to two sibling families, excluding 12 households where the sibling definition confounds the true family size. Columns Ib-IVb correspond to three sibling families, also excluding 17 households where the sibling definition confounds the true family size and 2 households with twins. Testing the null hypothesis of zero correlation between heterogeneity and covariates ($\pi = 0$), gives the following *p-values:* 0.579 (Column Va), 0.817 (Column VIa), 0.495 (Column VIIa), 0.326 (Column VIIIa), 0.075 (Column Vb), 0.100 (Column VIb), 0.273 (Column VIIb), and 0.220 (Column VIIIb).

4.6.2 Restricted sample: birthweight, PPVT score and "older" mothers

Another check of birth order effects and further controlling for endogeneity on fertility decisions, is to examine if parents adjust on time use margins after observing their children endowments. Two variables analysed previously (with established literature in family and birth order studies) are birthweight (S. Black et al., 2007; Del Bono, Ermisch, & Francesconi, 2012)(Del Bono, Ermisch, & Francesconi, 2012; Black et al., 2007) and cognitive outcomes (Conley, Pfeiffer, & Velez, 2007; Lehmann et al., 2016). I use PPVT score to proxy for cognitive outcome as this outcome was collected for both the Young Lives child and for a younger sibling.[112] Adding birthweight and age adjusted PPVT score[113] (in Table 33 below), only marginally affects the variability observed in the birth order coefficient for daily hours spent in leisure (from 0.328 to 0.271 hrs) and for hours spent in caring activities (from -0.808 to -0.773 hrs). A standard deviation increase in PPVT score amounts only to 0.088 hrs (5 min) more in time spent at school, and 0.132 hrs (8 min) less in time spent studying. Birthweight coefficients are almost zero (when rounded to the third decimal). Coefficients of birthweight and PPVT score reported in Table C9 in the Appendix.

To test if incomplete fertility could be at play in birth order effects, I estimate birth order effects for a sample where the mother is 28 years old at baseline and add birthweight as observed endowment. A caveat of this comparison is that the sample size dramatically shrinks by imposing the age restriction for mothers, representing only the 20% of the main analytic sample (265 vs. 1336). The direction of the birth order effect remains, but the magnitude shifts. The negative effect in hours spent at school increases (from -0.120 to -0.380 hrs) and becomes significant at the 5% level, while for hours spent in care decreases by half (from -0.808 to -0.481 hrs).

Furthermore, the zero-correlation hypothesis ($\pi = 0$) fails for Columns I, IV, and V. The Hausman-Taylor (HT) results (listed in Table C14 in the Appendix), show the coefficient for hours spent at school increases in both Column I (from -0.124 to -0.424 hrs) and Column IV (from -0.380 to -0.765 hrs), but the latter is no longer statistically significant. For hours spent in leisure (Column V), the coefficient increases (from 0.173 to 0.336 hrs). None of the HT estimates are statistically significant.

[112]Both birthweight and PPVT score were collected only for younger siblings (if present at the moment of the interview) and for a subsample of households. Thus, sample size is limited, and the known data restriction disclaimers apply for this section.

[113]I use an age adjusted PPVT outcome to make feasible comparisons among both siblings. The age reference is 4-6 years old, hence the information for PPVT scores for the Young Lives child comes from Round 2 of data collection, while the sibling's PPVT score may come from Round 3 or Round 4, if her/his age was between 4-6 years old.

Table 33. Sensitivity CRE: birthweight, PPVT score & mother's age

	Birthweight and PPVT score			Mom age (28+) and birthweight		
	Hrs/day at school	*Hrs/day in leisure*	*Hrs/day care*	*Hrs/day at school*	*Hrs/day in leisure*	*Hrs/day care*
	(I)	(II)	(III)	(IV)	(V)	(VI)
Birth order (j =2)	-0.124	0.271*	-0.773***	-0.380*	0.173	-0.481***
	(0.075)	(0.131)	(0.061)	(0.176)	(0.315)	(0.107)
p-value $H_0: \beta_1 = \beta_2 = 0$	0.099	0.039	0.000	0.030	0.582	0.000
R-squared	0.270	0.218	0.316	0.443	0.356	0.375
Observations	955	955	955	265	265	265

***p<0.001, **p<0.01, *p<0.05. Clustered robust standard errors at the family level in parentheses. Each column presents a separate regression. All regressions include controls listed in Table C9, plus birthweight (Columns I-VI) and age-adjusted standardised PPVT score (Columns IV-VI). Testing the null hypothesis of zero correlation between heterogeneity and covariates ($\pi = 0$), gives the following p-values: 0.004 (Column I), 0.086 (Column II), 0.862 (Column III), 0.002 (Column IV), 0.047 (Column V), and 0.460 (Column VI).

One last robustness test involves transforming the continuous time use outcome into percentage. In that way, we can incorporate time spent sleeping into the analysis and have the full 24-hour snapshot of time use activities among both siblings. Figure 2 depicts the proportion of the day the first and second born spent in each activity. Overall, there are not clear differences among activities, except for time spent in child work (0.036 percentage points difference); and the new insight regarding time spent sleeping, where most than 40% of the day is devoted to this activity. Estimating birth order effects with the transformed outcomes, findings in Table 34 are consistent with main results. The second born child spends less time in child work, 3.2% less of her/his day relative to her/his older sibling and more time in leisure activities.

Figure 6. Proportion of the day spent in each activity

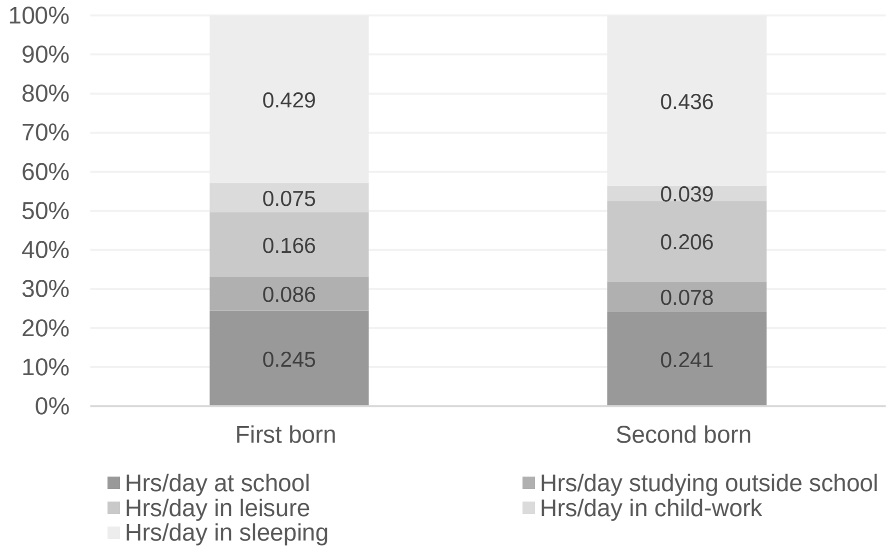

Table 34. Sensitivity CRE: Time use as percentage

	Prop. at school (I)	*Prop. studying outside school* (II)	*Prop. in leisure* (III)	*Prop. in child-work* (IV)	*Prop. sleeping* (V)
Birth order (j =2)	0.002	0.005**	0.018***	-0.032***	0.006*
	(0.003)	(0.003)	(0.005)	(0.004)	(0.003)
p-value $H_0: \beta_1 = \beta_2 = 0$	0.476	0.042	0.000	0.000	0.055
R-squared	0.279	0.214	0.294	0.364	0.263
Observations	1336	1336	1336	1336	1336

***p<0.001, **p<0.01, *p<0.05. Clustered robust standard errors at the family level in parentheses. Each column presents a separate regression. All regressions include controls reported in Table C17 in the Appendix. Testing the null hypothesis for zero correlation between heterogeneity and covariates ($\pi = 0$), gives the following *p-values:* 0.000 (Column I), 0.067 (Column II), 0.020 (Column III), 0.736 (Column IV), 0.541 (Column V).

After testing the robustness of the birth order findings with alternative specifications, is possible to confirm that the negative effect in child work for the second born sibling, particularly for hours spent in care, is robust for two child families. The negative effect holds for higher parity families, where similar negative effects in magnitude related to birth order are observed for the last born in three child families and is invariant when adjusting for PPVT score and birthweight.[114]

Evidence for time in educational activities remains mixed, while for time in leisure, only when augmenting the analysis to three children families we observe a positive effect for both, second and third born siblings. Nonetheless, these effects are smaller in magnitude when compared to the other variables in the specification and to the negative birth order effect in child work.

4.7 Investigating Mechanisms: Parental Educational Aspirations

This section attempts to unpack one potential mechanism driving the birth order differences in the previous section, and in doing so, complementing the literature linking the role of parental early aspirations for their children with time-use investments. Beyond the resource constraint, how parents (children) allocate differential investments, including time, in the household context, is linked to parental beliefs about the productivity and usefulness of those investments (O. Attanasio, Boneva, & Rauhn, 2018). As stated in Sections 4.1 and 4.2, there is still limited literature on how aspirations shape decision making (O. Attanasio & Kaufmann, 2014; Chiapa et al., 2012), and on parental perceptions about the returns to their time investments (O. Attanasio, Boneva, et al., 2018) (Cunha, Elo, & Culhane, 2013).

[114]Although, as discussed earlier, for the check on families with “complete” fertility (older mothers), the sample only represents 20% of the main analytic sample (265 vs. 1336 children-data points). The negative effect for the younger sibling sustains though its magnitude is almost reduced by half (from -0.808 to -0.481 hrs).

The main drawback of this section is only having information on parental aspirations for the Young Lives child and not for the rest of the siblings, reducing sample size and restricting to cross-sectional methods for the analysis. Despite this limitation, the comparison might improve our understanding of how household decisions are made, based on how parental aspirations vary by birth order, and how it may explain time use allocation.

Following previous studies, Table 35a displays the correlation matrix between birth order, holding the highest educational aspiration, i.e. a University/Postgraduate degree (UniPost) [115], PPVT score, and if child is a girl; while Table 35b shows the distribution of parental aspirations and the mean of the standardised PPVT score for both two and three child families with same-sex children. Although small in magnitude, we notice there is a negative association between birth order and parental aspirations, and positive relationship between birth order and PPVT score (significant at the 5% level). There is a positive correlation between UniPost parental aspiration and PPVT score, only significant for two-child families. For both family sizes, there is a small negative association between holding a UniPost aspiration and if child is a girl, but not statistically significant. Likewise, the proportion of children that parents have a UniPost parental aspiration is higher for the firstborn child, than for the second born, despite the latter having a higher PPVT score (when both children where about 4-6 years old). This holds for both two and three sibling families, though in all cases the percentages are quite high, where at least above 75% of parents aspire for a UniPost degree. For the third born child, the proportion for a UP degree parental aspiration is almost the same as for the second born child (slightly higher), but the difference with respect to her/his oldest sibling is not statistically significant. The second born child outperforms her/his oldest and youngest sibling, as measured by the PPVT score in both family sizes.

Table 35a. Correlation matrix of birth order and UniPost parental aspiration

	2 siblings				3 siblings			
	Birth order	University/ Postgraduate	Std PPVT	Child is female	Birth order	University/ Postgraduate	Std PPVT	Child is female
Birth order	1.000				1.000			
University/ Postgraduate	-0.276*	1.000			-0.224*	1.000		
Std PPVT	0.095*	0.098*	1.000		0.113*	0.025	1.000	
Child is female	-0.005	-0.046	0.028	1.000	0.013	-0.039	-0.049	1.000

***p<0.001, **p<0.01, *p<0.05.

[115] Young Lives original variable on parental aspiration distinguishes among different education levels, including No education, Grade 1-Grade 11, Vocational Education (incomplete and complete), Pedagogical Institution (incomplete and complete), University (incomplete and complete), and Postgraduate.

Table 35b. Means and difference in means of parental aspiration and Std. PPVT score

	2 siblings			3 siblings				
	First born (j =1)	Second born (j =2)	Diff. in means	First born (j =1)	Second born (j =2)	Third born (j =3)	Diff. in means (j =1 vs. j =2)	Diff. in means (j =1 vs. j =3)
University/ Postgraduate (prop.)	0.873	0.812	0.061**	0.847	0.750	0.776	0.093**	0.067
Standardised PPVT score	0.363	0.493	-0.130*	0.076	0.255	0.208	-0.179*	-0.132
Observations	760			504				

***p<0.001, **p<0.01, *p<0.05.

To inspect the relationship between birth order and parental educational aspirations for two and three child families of the same sex within a framework model, I use a probit model denoted in Eq (3):

$$Pr(\gamma_{ijft}=1 \mid (Birth\ order_{if} = j), x_{ift}) = \Phi(\theta_t + \beta_j(Birth\ order_{if} = j) + \varphi x_{ift} + \psi(Birth\ order_{if} = j) * \kappa_{ift}) \quad (3)$$

where Pr represents the probability of the parent holding the highest educational aspiration, a UniPost degree, defined as a binary indicator (equal to 1 for parents who aspire to obtain that degree, and 0 otherwise), for their child of birth order ($j = 2, 3$) with respect to the firstborn child ($j = 1$) (omitted category); ψ is an interaction term parameter capturing differences of birth order by age adjusted PPVT score included in κ_{ift}; x_{ift} denotes a vector of family/child/household characteristics described in Section 2.

Furthermore, I estimate and extended version of Eq (2) examining the joint role of lagged parental aspirations (when child was about five years old) and birth order as determinants of time-use allocation as depicted in Eq (4):

$$\gamma_{ift} = \theta_t + \beta_j(Birth\ order_{if} = j) + \tau P_{ift-2} + \vartheta(Birth\ order_{if} = j) * P_{ift-2} + \varphi x_{ift} + \varrho\kappa_{ift} + \alpha z_{ft} + \pi\bar{x}_f + v_f + \varepsilon_{ift} \quad (4)$$

where Y_{ift} is hours spent at school or hours spent in care[116]; τ denotes the parameter for the binary indicator of the lagged UniPost parental aspiration ($P = 0{,}1$); ϑ is the interaction term parameter, capturing differences of parental aspirations ($P = 0{,}1$) by birth order ($j = 2, 3$) with respect to the first born ($j = 1$); and κ_{ift} is the age-adjusted PPVT score.

[116]Only looking at these outcomes given the persistent negative effect for child work and the mixed evidence for time use in education.

In Table 36a I report the Average Marginal Effect (AME) for Eq (3). Results align with the correlations obtained earlier in Table 9a. There is a negative association between birth order and parental aspirations for a UniPost degree for both family sizes, but in this case, none is statistically significant. Compared to firstborns, second and third born siblings are respectively 9.6 and 12 percentage points less likely that parents aspire for them to have a UniPost degree. PPVT age adjusted score is only relevant for two children families (Column I), where one standard deviation increase in the score leads to 5.7 percentage points more likely that parents aspire for a UP degree for their second born child. The average marginal effects of the rest of the predictors in the model provide are reported in Table C10 in the Appendix.

Table 36a. Average Marginal Effects: Parental aspirations and birth order

	2 siblings	3 siblings
	University/ Postgraduate (I)	*University/ Postgraduate* (II)
Birth order (j =2)	-0.048 (0.034)	-0.082 (0.060)
Birth order (j =3)		-0.068 (0.051)
Std PPVT score	0.057** (0.017)	0.053 (0.043)
p-value $H_0: \beta_1 = \beta_2 = 0$ & $\psi_1 = \psi_2 = 0$ | $\beta_1 = \beta_2 = \beta_3 = 0$ & $\psi_1 = \psi_2 = \psi_3 = 0$	0.293	0.013
Observations	760	504

***p<0.001, **p<0.01, *p<0.05. Standard errors in parentheses. Each column represents a separate probit regression. Testing the null hypothesis of zero correlation between heterogeneity and covariates ($\pi = 0$), gives the following *p-values*: 0.296 (Column I) and 0.805 (Column II).

I proceed to estimate Eq (4) only for two children families, given the shrinkage in sample size denoted in Table 36a above for three-child families. Effectively, there are no differences in time spent in care if parents aspire or not for a UniPost degree for their second born child. The youngest sibling spends between 0.742 and 0.753 hrs (~45 min) less in caring activities. Conditioning on parental aspiration, the coefficient for time spent in care remains virtually unchanged with respect to the estimate in Table 36b (Column Ia) (-0.787 hrs). The coefficient for time-spent at school does vary if parents do not hold the highest educational aspiration. The daily number of hours spent at school for the youngest child decreases from 0.175 (11 min) to 0.515 hrs (31 min) in contrast with her/his oldest sibling but the difference is not statistically significant. Average marginal effects for the rest of the predictors are reported in Table C11 in Appendix.

Table 36b. Average Marginal Effects: Joint effect parental aspirations and birth order

	2 siblings	
	Hrs/day at school (I)	*Hrs/day care* (II)
Birth order (j =2)	-0.226* (0.098)	-0.751*** (0.071)
University/Postgrad (p =1)	0.164 (0.144)	-0.050 (0.091)
Birth order (j =2)* University/Postgrad (p =0)	-0.515 (0.325)	-0.742*** (0.162)
Birth order (j =2)* University/Postgrad (p =1)	-0.175 (0.095)	-0.753*** (0.073)
p-value $H_0: \beta_2 = \tau_2 = \vartheta_{21} = 0$	0.106	0.000
R-squared	0.168	0.326
Observations	760	760

***p<0.001, **p<0.01, *p<0.05. Clustered robust standard errors at the family level in parentheses. Each column presents a separate regression. Testing the null hypothesis of zero correlation between heterogeneity and covariates ($\pi = 0$), gives the following *p-values*: 020 (Column I) and 0.432 (Column II).

After this section, we can highlight two results. First, parents are equally likely to aspire for the highest level of education, a UniPost degree, regardless to birth order. This finding holds for two and three children families; and second, even after conditioning for parental aspirations, the negative relationship of birth order and time spent in child work, i.e. care activities, for the second born remains.

4.8 Conclusions

The importance of time in the production of skills and other child outcomes is increasingly recognised in the literature. Although, there is still limited understanding of child's time use as one input or channel for skill development and human capital transmission. This chapter documents the relationship between birth order and child's time use. There are two main motivations for the analysis in this chapter. One is due to the wide variation in findings in the previous literature examining the role of birth order with children's outcomes. The second is the little attention child's time use has received considering: a) a more comprehensive list of time allocation activities; and b) an expanded conceptualisation of child work, including time for household production. The identification strategy to overcome endogeneity of family size and estimate causal effects relies on examining this relationship for two-child families and identification across households.

I find that higher birth order has a significant and negative effect on child work. In a two-sibling family, the second born child is 10.8 percentage points less likely to participate in child work; and spending 0.81 hours (about 49 minutes) less in care activities of other household members (e.g. younger siblings, elderly, or members with disabilities). The results on child work are robust to a range of specifications including time use as different outcomes (e.g. as binary indicators, continuous outcomes, and as percentage measures), variations in family size (e.g. two versus three siblings), observed endowments (e.g. birthweight and cognitive score), families with “complete” fertility decisions, and irrespective of parental educational aspirations for both siblings. The magnitude of the effect is substantial when compared to other predictors in the model and other previous studies. Furthermore, looking to a broader range of time use activities, it seems the time unspent in child work is reallocated in expanded time spent in leisure rather than time spending at school or studying. I found no conclusive evidence of birth order effects for school participation and time spent in educational activities (school or studying). According to Moshoeshoe (2016), education effects related to birth order in developing countries, seem to be context-specific and linked to each country level of development.

When probing the child work results and examining if parental educational aspirations influence time investments, I find that parents hold the highest parental aspiration (e.g. a University/Postgraduate degree) regardless of birth order; and that holding that educational aspiration do not affect time use allocation between first and second born siblings at least for child work.

The findings on the negative effect of child work and higher birth order siblings endorse the hypothesised negative relationship and are in line with previous evidence for developing countries (Ejrnæs & Pörtner, 2004; Emerson & Souza, 2008; Moshoeshoe, 2016; Seid & Gurmu, 2015). Concerning the relation between birth order and educational time-inputs, we are not able to confirm or reject the relationship to any direction, maintaining the uncertainty conclusion related to this type of inputs and developing countries. Likewise, at least in the case of Peru, we reject the hypothesis that parental aspirations vary by birth order. Although an interesting result by itself, it does not help to explain the factors driving the negative effect on child work and younger siblings and to shed light on the unclear relationship amid birth order and time-inputs related to education. It is advisable to remember the sample restrictions encounter in this section of the analysis.

We could argue that time is an input controllable by families and relatively easy to adjust. All these results have implications on how this distribution/redistribution of time use, in turn, affects other child’s outcomes. When we put in context the negative relationship between child work and birth order looking into weekly and monthly hours, the second born child spends around four weekly hours less than her/his firstborn sibling in child work related to care activities, which in turn amounts to 16 hours per month. What could a child achieve if having 16 hours to spare with her/his time? Conversely, what do the firstborn child could achieve if having 16 hours to spare with her/his time?

There is a significant focus on policies aiming to increase quantity/quality to school (e.g. extending the length of the school day) and on policies to reduce child work, with narrow emphasis on labour market work. According to Keane, Krutikova, and Neal (2018) policies to reduce child work will only lead to gains in human capital if they nudge families to reallocate the freed-up time to the subset of possible alternative activities that are more productive than working. There is also increasing awareness that some children's work can be benign or even beneficial (concerning skills), and child contributions may be vital for household survival, particularly among the poorest families (Morrow & Boyden, 2018). One priority should be to incorporate time use for household production in the definition and measurement of child work. Likewise, there is still much scope to design and implement more integrated efforts to reduce the pressure of care work experienced by firstborn children, particularly at school-age stages crucial to child development. Schooling is essential for human capital formation, and it is a human capital investment which mainly happens during childhood.

Although we can claim that the negative birth order effect for child work (effectively hours spent in caring activities) is an internally valid result, it comes with a cost on the external validity for larger family sizes (e.g. more than three children). However, similar results are encountered in studies examining birth order and child market labour participation, where higher birth order children are less likely to participate in labour (Moshoeshoe, 2016; Seid & Gurmu, 2015). Intuitively, the negative effect in child work for higher birth order siblings makes sense given the inverse relationship nature of birth order with age. Furthermore, findings from the analysis can be generalised to other middle-income countries with similar socioeconomic context, large levels of inequalities, and historical high incidence of child work participation as Peru.

Neglecting measurement error can result in misleading conclusions. There is more scope to improve issues on measurement error related to time use data. Possible solutions include explicitly listing a more extensive set of activities for the 24-hour day (e.g. pertinent to the broad concept of the activities included under the "leisure" construct within the Young Lives data) and collect time use data for both typical a day and a weekend day. Other solutions involve alternatives in the time use data collection like employing time use diaries for the person and sending text messages as reminders to fill out the information. This technique has been proven cost-effective to enhance participation. Likewise, further research is needed to examine other potential mechanisms explaining household dynamics and behaviours in resource allocation.

Chapter 5 Discussion, Conclusions, and Policy Implications

As established in chapter 1, the present thesis contributes to a better understanding on three essential aspects related to skill development: the use of early childhood scalable interventions to understand childcare choices, time allocation as an input to foster skills, and the family structure as a determinant of time investments. Understanding the process of human capital accumulation and skill development in contexts with persistent levels of inequalities is crucial if we aim that low-income children exposed to high-risk factors (e.g. poverty, malnutrition, low education levels) succeed in life and reach their full potential. Colombia and Peru share a combination of unique characteristics to analysing the role of the family and child investments in the process of skill development among low-income children. I organise this final chapter as follows. First, I highlight the key findings across the three empirical chapters. Second, taking together these results and coupled with previous findings on related literature, I discuss some lessons based on the evidence and advise some policy implications. Finally, I point out the main limitations on the present analyses and suggests some potential lines of research.

5.1 Main findings

Chapter 2 constitutes the first attempt to exploit the experimental study design of an early childhood visiting programme to examine childcare choices for SES disadvantaged population. The evidence shows that the stimulation intervention led to an increase of informal childcare (4.6 percentage points) and no impact for the rest of childcare outcomes, relative to maternal care. The stimulation treatment effect is robust to the inclusion of different covariates, including a child's development score. We also document evidence that the intervention led to an increase in playtime for maternal care, consistent with earlier findings in Attanasio et al. (2017).

On the positive impact on informal childcare, this result might be reflecting that parents perceived the stimulation treatment increased the child's skills and would not benefit from being in a more formal childcare setting. This is consistent with the complementarity feature central to the dynamic model of skill formation (Cunha & Heckman, 2008). Another explanation is that the stimulation intervention delivered information to the parents about their child's skills, increasing parental confidence and their knowledge in child nurture, hence supplementing the need for formal childcare and using informal care arrangements instead to save costs. In this scenario, the stimulation treatment might be acting simultaneously as a substitute for childcare and complement of parents' knowledge. Alternatively, the result is indicating parental preferences for "internal" childcare arrangements. Mothers may be less willing to entrust their children to institutions and may prefer either to care for the children themselves or to have them in the custody of relatives, especially when they are very young (Arpino et al., 2012).

On the null results of the stimulation treatment for the rest of the childcare outcomes, one reason might relate to the intervention's original design, as it was not conceived to detect any effect on childcare outcomes. Another explanation could be the relatively short exposure to the intervention, only lasting 18 months and failing to provide with comprehensive information on various redistributions of parental investments they could implement. This explanation is linked to the first reason, as 18 months were conceived to have an impact on child development, measured through the Bayley scales, nor on informing about the potential advantages (disadvantages) on the choice of care. A third reason involves the small percentage of children distributed among the different types of childcare examined, in contrast with the large proportion of children being taken care of by their mothers, regardless of treatment allocation.

Chapter 3 complements the recent studies (Borga, 2018; Keane et al., 2018) examining child's time investments to foster skill production. I find that time inputs are marginal for both cognitive and psychosocial skills, but we document relevant differences in the type of activities influencing each outcome by age. The latter confirms that the production functions for each skill are different, as established in earlier literature (Cunha & Heckman, 2008; Del Bono et al., 2016). Consistent with previous studies, we find that time in educational activities, such as the time spent studying and at school during the school-age period and when transitioning into adolescence is crucial for verbal (cognitive) development. The results indicate that an extra hour spent studying per day is slightly more productive than extra daily hours spent at school for the verbal score. For the Self-Esteem Index, current time (at age 15) spent in leisure and past (at age 8) and current time spent in child work is detrimental for this skill at age 15, decreasing this outcome between 0.057 and 0.63 standard deviations, respectively. We report concerns on measurement error for the Self-Efficacy Index, excluding the results in the discussion.

On the trade-off analysis of child work, we only find small detrimental effects of current time spent in paid work (at age 15), particularly when it crowds-out time spent in educational activities for the verbal score and no effects for the Self-Esteem Index.

In chapter 4, I find that higher birth order has a significant and negative effect on child work. In two-children families, the second born child is 10.8 percentage points less likely to participate in child work; and spending 0.81 hours (about 49 minutes) less in care activities of other household members (e.g. younger siblings, elderly, or members with disabilities). The results on child work are robust to a range of specifications including time use as different outcomes (e.g. as binary indicators, continuous outcomes, and as percentage measures), variations in family size (e.g. two versus three siblings), observed endowments (e.g. birthweight and cognitive score), families with "complete" fertility decisions, and irrespective of parental educational aspirations for both siblings. The magnitude of the effect is substantial when compared to other predictors in the model and other previous studies. Furthermore, looking to a broader range of time use activities, the time unspent in child work by the younger sibling is reallocated in expanded time spent in leisure rather than time spending at school or studying. I found no conclusive evidence of birth order effects for school participation and time spent in educational activities (school or studying).

5.2 Lessons and Policy implications

The listed findings on this thesis, coupled with previous related research, lead us to draw the following lessons and policy implications for LMIC sharing similar characteristics with Colombia and Peru. Previous investigations demonstrate that tackling inequalities early on in the life-cycle is the most cost-effective strategy to stop the intergenerational transmission of poverty. Research suggests that for SES disadvantaged children, each USD 1 devoted to effective early childhood programmes in developing countries, leads to USD 2–23 in future savings (Bialik, 2012; Heckman, 2011). Furthermore, findings from empirical research indicate early childhood interventions in developing countries are likely to be more effective if they are comprehensive (e.g. they include health, nutrition, and stimulation), run for longer, have greater intensity (e.g. higher frequency and longer duration of contacts), use a structured curriculum, and enable parents and children to participate together to practise stimulation activities and receive feedback (Engle et al., 2011; S. M. Grantham-McGregor et al., 2014; Yousafzai et al., 2014). Investigating mediation variables to reduce SES gaps, Rubio-Codina et al. (2016) document parental education, particularly maternal education, and the quality of the home environment, mediated the SES gap (about 0.5 of a standard deviation in cognition and language) in all outcomes examined for children between 6–42 months in low- and middle-income families in Bogota. These gaps substantially widen with age, hence tackling them early in life contribute to future savings in more expensive remediation interventions.

Another lesson from the literature points that process quality enhancements, such as the integration of a structured curriculum and improved interactions between caregivers and children supported by a coaching and mentoring, have more cost-effective impacts, with respect to improvements in the so-called structural quality alone (e.g. changes in infrastructure or staffing) (O. Attanasio, Baker-Henningham, et al., 2018). Likewise, it is essential to have a more comprehensive understanding of informal childcare services, particularly for the low-income population. This type of care should be included in the discussion of public childcare, as it is usually overlooked because it has been seen purely as a “family matter,” and hence not of interest to public policy (Bryson et al., 2013). Still, earlier findings have shown that the use of informal childcare, particularly grandparents, significantly increases mothers’ labour participation, with stronger effects in disadvantaged families (Arpino et al., 2012; Posadas & Vidal-Fernández, 2012). The results in chapter 2 hint to the possibility of using the early childhood intervention as an instrument to explore the causal impact of informal childcare in later life outcomes from the child or longer-term effects in maternal labour participation. The results also indicate that the effectiveness of scaled interventions (i.e. using pre-existing conditions and infrastructure), based on experimental study design, might be a promising cost-effective approach to investigate parental decisions (i.e. investments) and overcome the endogeneity issues intrinsic to these decisions, while at the same time, promoting future investments in human capital. The SDGs call for all children to "have access to quality early childhood development, care, and pre-primary education so that they are ready for primary education" by 2030. Achievement of the SDGs requires greater coordination of early child development programming within the existing health and educational infrastructure, with attention to the quality of services and sustained parental education (Özler et al., 2018).

There is a significant focus on policies related to increasing quantity/quality to school (e.g. extending the length of the school day) and on policies to reduce child work, with narrow emphasis on labour market work only. Policies to reduce child work will only lead to gains in human capital if they nudge families to reallocate the freed-up time to the subset of possible alternative activities (i.e. education in the case of Peruvian children) that are more productive than working in fostering skills (Keane et al., 2018).

Another lesson is that finding appropriate measures or scales for psychosocial skills, suitable and adaptable to different local contexts is challenging. Greater efforts should be implemented, from academia and the government, to conduct studies aiming to validate, collect and measure psychosocial skills. This is crucial if we aim to document the causal processes and mechanisms for skill formation in these types of skills, and also relevant to the design of developmentally timed interventions.

Finally, if we aim to develop and implement comprehensive interventions that lead to sustained effects on fostering and developing skills, it is essential to think about the process of skill formation in a more systematic way. It implies recognising which are the essentials elements to focus on enhancing abilities that also need to be developed in the next level and so on.

5.3 Limitations and future lines of research

Although we do not want to undermine the relevance of the present findings, it is important to recognise the limitations. Findings in chapter 2 are constrained to the stimulation intervention only, affecting the external validity of the conclusions. However, the impact of the stimulation treatment in childcare choices is robust to different specifications and after accounting for many predictors, including a cognitive score. Likewise, despite the stimulation treatment increased informal childcare use, and findings from previous evaluations (O. Attanasio et al., 2017; O. Attanasio et al., 2014) demonstrate it improved cognitive and language outcomes, the results on chapter 2 do not allow to examine the causal impact of childcare in other child's outcomes. These results complement previous early childhood literature showing that successful interventions alter parental behaviour. Understanding why this happens, how good parenting practices can be promoted, and through which channels parenting influences child development are crucial tasks for upcoming studies (Heckman & Mosso, 2014). Future analyses should focus on identifying profiles and characteristics of informal childcare providers to understand potential mechanisms that drive this impact and enhance the effectiveness of early childhood interventions in outcomes of interest.

For chapter 3, the issue of measurement error in the psychosocial indicators hints that better efforts should be made to find appropriate scales and constructs to measure this type of skills. It should incorporate age-appropriate items and better adaptability to the local context. This implies a closer collaboration among disciplines, particularly the economics and psychology fields. An alternative would be that instead of measuring multidimensional constructs, researchers should settle to measure one domain or one specific trait, or multiple specific traits until suitable multidimensional measures are developed for deprived populations in LMIC. For cognitive skills, progress on exploring shorter, precise, and cost-effective measures to employ at scale in LMIC is examined in Rubio-Codina, Araujo, Attanasio, & Grantham-McGregor (2016). One finding in this study is that measuring gross motor in children younger than 19 months and language development in children older than 19 months is valid using shorter versions. A similar exercise should be explored to identify critical domains for psychosocial skills in order to apply shorter or more appropriate scales to measure them.

Likewise, and linked to both chapters 3 and 4, there is still much scope for improvement in time use data collection. Possible solutions include explicitly listing a more extensive set of activities for the 24-hour day (e.g. pertinent to the broad concept of the activities included under the "leisure" construct within the Young Lives data) and collect time use data for both typical a day and a weekend day. Other solutions involve alternatives in the time use data collection like employing time use diaries for the person and sending text messages as reminders to fill out the information. This technique has been proven cost-effective to enhance participation. Likewise, further research is needed to examine other and more potential mechanisms explaining household dynamics and behaviours in resource allocation. The latter is relevant if we aim to disentangle and identify additional pathways to tackle inequalities in human capital and foster skill development.

A consistent finding among the human capital literature is that differential investment along the life-cycle translate into variations or ability gaps, which in turns lead to inequalities in economic and social outcomes (Cunha, 2014). Overall, the topics investigated in this thesis have important implications to enhance our understanding of the human capital development process for the disadvantaged population. In particular, it discovers important considerations to foster and enhance abilities for children early in life. There is still room to expand the scope and understanding on how this dynamic and fluid process works and the weight of factors (environment) and actors (teachers, parents, children) role, particularly for psychosocial skills.

In the education field, there is always pressure on developing innovative approaches to enhance learning and abilities during instructional time or in extra-classes. Despite the different debates and arguments on the importance on one type of abilities over the other (i.e. cognitive skills versus psychosocial skills), at the end of the day, the joint agreement is what matters most is the children. Giving them the right tools (and abilities) to succeed in life, despite their different backgrounds and experiences, should be the overarching aim. However, if we want to enable children to reach their full potential as adults, to develop a high-skilled and productive work-force, we need to keep learning on which abilities since early age are relevant for predicting later-life outcomes. Not only focusing on outcomes about employability, income or educational attainment, but also about health, life satisfaction, mental illness, crime, and many others that are relevant for a successful, healthy and productive adult life.

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Appendix

Table A1. Average Marginal Effects (all coefficients)

	Public Childcare		Private Childcare		Informal Childcare	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
Stimulation	-0.067	-0.034	-0.017	-0.017	0.044*	0.046*
	(0.057)	(0.052)	(0.014)	(0.012)	(0.019)	(0.018)
Public Childcare (BL)	0.456***	0.112	0.023	0.080	-0.044***	-0.044***
	(0.102)	(0.115)	(0.027)	(0.103)	(0.008)	(0.009)
Private Childcare (BL)	0.329***	0.158	0.047	0.080	0.028	0.048
	(0.095)	(0.109)	(0.041)	(0.103)	(0.051)	(0.052)
Informal Care (BL)	0.114*	0.257**	0.027	-0.000	0.376***	0.160*
	(0.069)	(0.082)	(0.037)	(0.019)	(0.065)	(0.070)
Boy		-0.036		-0.007		-0.003
		(0.034)		(0.015)		(0.018)
Age (months)		-0.069*		0.007		0.005
		(0.042)		(0.013)		(0.023)
Age sq. (months)		0.002*		0.000		0.000
		(0.001)		(0.000)		(0.001)
Mother's education		0.003		0.005**		0.000
(years)		(0.006)		(0.002)		(0.002)
Mother is occupied		0.069**		0.005		0.006
		(0.035)		(0.013)		(0.019)
Main caregiver is single		0.051		0.009		0.036
		(0.048)		(0.016)		(0.022)
Any childcare before BL		0.270***		-0.023		-0.013
		(0.038)		(0.023)		(0.021)
Grandparent in HH		-0.039		0.008		0.016
		(0.417)		(0.012)		(0.021)
Wealth Index		-0.010		-0.002		-0.002
		(0.010)		(0.003)		(0.005)
Number of Children		-0.031		-0.010		0.015*
aged 6 years-old or younger		(0.029)		(0.010)		(0.009)
Joint Sig Test	0.075	0.039	0.075	0.039	0.075	0.039
R-squared	0.101	0.154	0.101	0.154	0.101	0.154
Observations	632	616	632	616	632	616

*p<0.05, **p<0.01, ***p<0.001 Table shows coefficients for two separate regressions (a) and (b). Standard errors in parentheses are adjusted for clustering at municipality level.

Table A2. Marginal Effects

	Public Childcare		Private Childcare		Informal Childcare	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
Stimulation	-0.064	-0.031	-0.017	-0.012	0.018*	0.016*
	(0.064)	(0.064)	(0.016)	(0.010)	(0.008)	(0.007)
Public Childcare (BL)	0.458***	0.142	0.022	0.055	-0.041***	-0.035***
	(0.102)	(0.138)	(0.026)	(0.074)	(0.008)	(0.009)
Private Childcare (BL)	0.336***	0.199*	0.046	0.021	0.025	0.042
	(0.093)	(0.121)	(0.041)	(0.042)	(0.047)	(0.046)
Informal Care (BL)	0.117*	0.310***	0.025	-0.000	0.375***	0.144*
	(0.071)	(0.089	(0.037)	(0.011)	(0.069)	(0.069)
Boy		-0.049		-0.004		-0.001
		(0.043)		(0.010)		(0.006)

	Public Childcare		Private Childcare		Informal Childcare	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
Age (months)		-0.084		0.004		0.002
		(0.054)		(0.009)		(0.008)
Age sq. (months)		0.002		0.000		0.000
		(0.002)		(0.000)		(0.000)
Mother's education (years)		0.006		0.003**		0.000
		(0.007)		(0.001)		(0.001)
Mother is occupied		0.092**		0.003		0.002
		(0.043)		(0.009)		(0.006)
Main caregiver is single		0.082		0.007		0.012*
		(0.060)		(0.011)		(0.007)
Any childcare before BL		0.333***		-0.014		-0.004
		(0.054)		(0.014)		(0.007)
Grandparent in HH		-0.041		0.005		0.005
		(0.062)		(0.008)		(0.007)
Wealth Index		-0.015		-0.002		-0.001
		(0.012)		(0.002)		(0.002)
Number of Children aged 6 years-old or younger		-0.037		-0.006		0.005*
		(0.036)		(0.007)		(0.003)
Joint Sig Test	0.075	0.039	0.075	0.039	0.075	0.039
R-squared	0.101	0.154	0.101	0.154	0.101	0.154
Observations	632	616	632	616	632	616

*p<0.05, **p<0.01, ***p<0.001 Table shows coefficients for two separate regressions (a) and (b). Standard errors in parentheses are adjusted for clustering at municipality level.

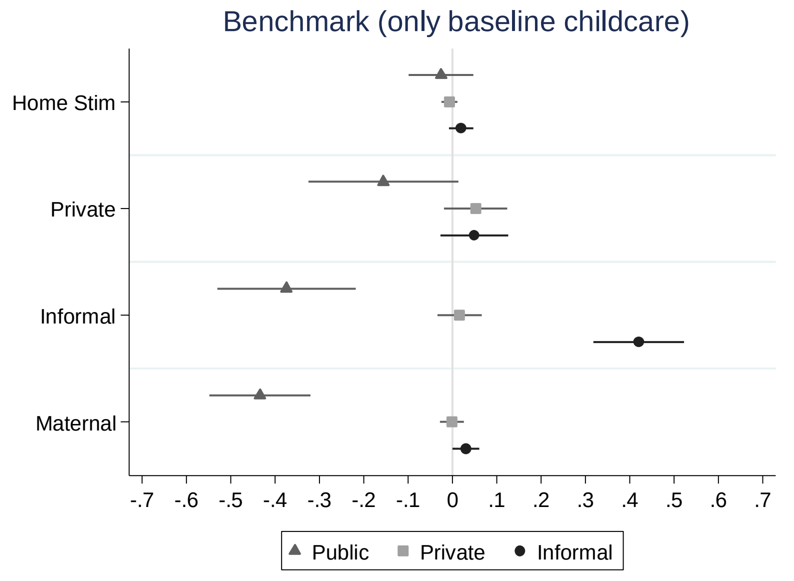
Table A3. Average Marginal Effects

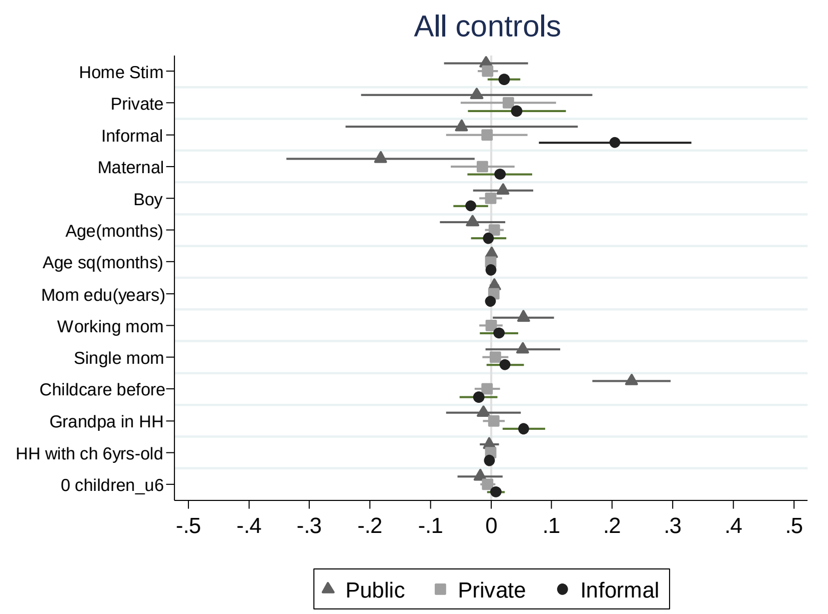
	Public Childcare		Private Childcare		Informal Childcare	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
Stimulation	-0.025	-0.008	-0.007	-0.006	0.020	0.021
	(0.037)	(0.035)	(0.009)	(0.008)	(0.014)	(0.014)
Public Childcare (BL)	-0.156	-0.024	0.052	0.029	0.050	0.042
	(0.086)	(0.098)	(0.036)	(0.040)	(0.039)	(0.041)
Private Childcare (BL)	-0.374***	-0.049	0.016	-0.007	0.421***	0.205***
	(0.080)	(0.098)	(0.026)	(0.034)	(0.052)	(0.064)
Informal Care (BL)	-0.434***	-0.182*	-0.001	-0.014	0.030*	0.014
	(0.058)	(0.079)	(0.014)	(0.027)	(0.015)	(0.027)
Boy		0.020		-0.001		-0.033*
		(0.025)		(0.010)		(0.015)
Age (months)		-0.031		0.005		-0.004
		(0.028)		(0.008)		(0.015)
Age sq. (months)		0.001		-0.000		0.000
		(0.001)		(0.000)		(0.000)
Mother's education (years)		0.006		0.004*		-0.001
		(0.004)		(0.002)		(0.002)
Mother is occupied		0.054*		-0.000		0.013
		(0.026)		(0.010)		(0.016)
Main caregiver is single		0.052		0.007		0.023
		(0.032)		(0.011)		(0.016)
Any childcare before BL		0.232***		-0.006		-0.021
		(0.033)		(0.011)		(0.016)
Grandparent in HH		-0.013		0.005		0.054**
		(0.031)		(0.009)		(0.018)

	Public Childcare		*Private Childcare*		*Informal Childcare*	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
Wealth Index		-0.003		-0.000		-0.002
		(0.008)		(0.003)		(0.004)
Number of Children aged 6 years-old or younger		-0.018		-0.005		0.008
		(0.019)		(0.006)		(0.007)
Joint Sig Test	0.489	0.458	0.489	0.458	0.489	0.458
Pseudo R-squared	0.085	0.123	0.085	0.123	0.085	0.123
Observations	1,258	1,230	1,258	1,230	1,258	1,230

*p<0.05, **p<0.01, ***p<0.001 Table shows coefficients for two separate regressions (a) and (b). Standard errors in parentheses are adjusted for clustering at municipality level.

Figure A4. Average Marginal Effects





*Each figure shows coefficients for two separate regressions.

Table A5. Logit Average Marginal Effects (all coefficients)

	Any Childcare	
	(1a)	(1b)
Stimulation	-0.049	-0.017
	(0.051)	(0.049)
Any Childcare (BL)	0.436***	0.245***
	(0.045)	(0.067)
Boy		-0.047
		(0.038)
Age (months)		-0.045
		(0.049)
Age sq. (months)		0.001
		(0.001)
Mother's education (years)		0.007
		(0.006)
Mother is occupied		0.081*
		(0.036)
Main caregiver is single		0.093
		(0.050)
Any childcare before BL		0.211***
		(0.039)
Grandparent in HH		0.006
		(0.052)
Wealth Index		-0.014
		(0.010)
Number of Children aged 6 years-old or younger		-0.013
		(0.026)
Joint Sig Test	0.342	0.724
Pseudo R-squared	0.088	0.127
Observations	636	620

*p<0.05, **p<0.01, ***p<0.001 Table shows coefficients for two separate regressions (a) and (b). Standard errors in parentheses are adjusted for clustering at municipality level.

Table A6. Cronbach's alpha for Bayley's aggregate index subscales

Subscale	**Baseline**	**Follow-up**
Cognitive	0.915	0.824
Receptive language	0.915	0.836
Expressive language	0.926	0.842
Fine moter	0.917	0.833
Gross motor	0.923	0.881
Test scale	0.934	0.871

* Table shows Cronbach's alpha for baseline and follow-up data.

Table A7. Bayley's aggregate index: Average Marginal Effects

	Public Childcare	*Private Childcare*	*Informal Childcare*
	(1b)	(2b)	(3b)
Stimulation	-0.033	-0.017	0.046*
	(0.052)	(0.012)	(0.019)
Public Childcare (BL)	0.134	0.058	-0.044
	(0.120)	(0.072)	(0.009)
Private Childcare (BL)	0.169	0.026	0.048
	(0.109)	(0.056)	(0.055)

	Public Childcare (1b)	*Private Childcare* (2b)	*Informal Childcare* (3b)
Informal Care (BL)	0.263***	-0.002	0.158*
	(0.080)	(0.018)	(0.070)
Boy	-0.039	-0.005	-0.003
	(0.035)	(0.014)	(0.018)
Age (months)	-0.059	0.003	0.005
	(0.043)	(0.016)	(0.023)
Age sq. (months)	0.002	-0.000	-0.000
	(0.001)	(0.000)	(0.001)
Mother's education (years)	0.004	0.004	0.000
	(0.006)	(0.002)	(0.002)
Mother is occupied	0.069*	0.005	0.006
	(0.035)	(0.012)	(0.019)
Main caregiver is single	0.052	0.010	0.036
	(0.048)	(0.016)	(0.022)
Any childcare before BL	0.267***	-0.022	-0.013
	(0.038)	(0.022)	(0.021)
Grandparent in HH	-0.040	0.008	0.016
	(0.048)	(0.012)	(0.021)
Wealth Index	-0.009	-0.003	-0.002
	(0.010)	(0.003)	(0.005)
Number of Children aged 6 years-old or younger	-0.035	-0.008	0.016
	(0.027)	(0.009)	(0.009)
Bayley Cognitive Index	-0.028	0.012	0.001
	(0.041)	(0.014)	(0.018)
Joint Sig Test	0.052	0.052	0.052
Pseudo R-squared	0.155	0.155	0.155
Observations	616	616	616

*p<0.05, **p<0.01, ***p<0.001 Standard errors in parentheses are adjusted for clustering at municipality level.

Table A8. Factor Analysis

	Baseline		*Follow-up*	
	Factor1	Uniqueness	Factor1	Uniqueness
Caregiver play alone with child and her/his toys	0.317	0.900	-0.030	0.999
Caregiver dance/draw alone with child	0.221	0.951	-0.048	0.998
Caregiver read/tell stories alone to child	0.218	0.953	-0.087	0.993
Caregiver play outside with child	0.196	0.962	0.119	0.986
Caregiver play with child & other kids	0.458	0.790	0.626	0.608
Caregiver dance/draw with child & other kids	0.368	0.865	0.500	0.750
Caregiver read/tell stories to child & other kids	0.279	0.922	0.407	0.835
Eigenvalue		0.658		0.831
(Akaike's) AIC		244.830		278.205
Observations		1785		1599

*Factor analysis for the analytic sample retaining one factor.

Table A9. OLS: Play time

	Play activities (1)	*Factor Index* (2)	*Hrs of play* (3)
Treatment Group	0.257	0.106	0.031
	(0.197)	(0.168)	(0.197)
Public childcare (BL)	-0.206	-0.085	-0.100
	(0.290)	(0.200)	(0.304)
Private childcare (BL)	-0.774**	-0.569*	-0.777**
	(0.223)	(0.215)	(0.215)
Informal childcare (BL)	-0.043	-0.275	-0.006
	(0.350)	(0.266)	(0.348)
Boys (=1 if male)	0.104	-0.035	0.075
	(0.129)	(0.095)	(0.111)
Age (months)	0.133	0.144	0.073
	(0.130)	(0.094)	(0.184)
Age sq. (months)	-0.004	-0.004	-0.003
	(0.004)	(0.003)	(0.005)
Mother total years of education at BL	0.036*	0.026*	0.054**
	(0.014)	(0.012)	(0.017)
Employed mother at BL	0.034	-0.060	-0.113
	(0.104)	(0.093)	(0.119)
Single mother at BL	-0.019	0.066	-0.005
	(0.136)	(0.107)	(0.127)
Any childcare before BL	0.154	0.289	0.103
	(0.212)	(0.197)	(0.201)
Grandparent in HH	-0.104	-0.169	-0.222
	(0.139)	(0.097)	(0.124)
Wealth index[3]	0.053	0.028	0.046
	(0.035)	(0.017)	(0.031)
Number of Children aged 6 years-old or younger	-0.002	0.357**	-0.020
	(0.071)	(0.071)	(0.070)
Baseline outcome (number play activities, factor index, total hours of play)	0.207**	0.127*	0.109**
	(0.040)	(0.052)	(0.036)
Constant	-0.367	-1.793**	0.296
	(1.069)	(0.748)	(1.521)
R-squared	0.101	0.100	0.077
Prob>F	0.20	0.53	0.88
Observations	574	574	574

*p<0.05, **p<0.01, ***p<0.001 Each row represents a separate regression. Standard errors in parentheses are adjusted for clustering at municipality level.

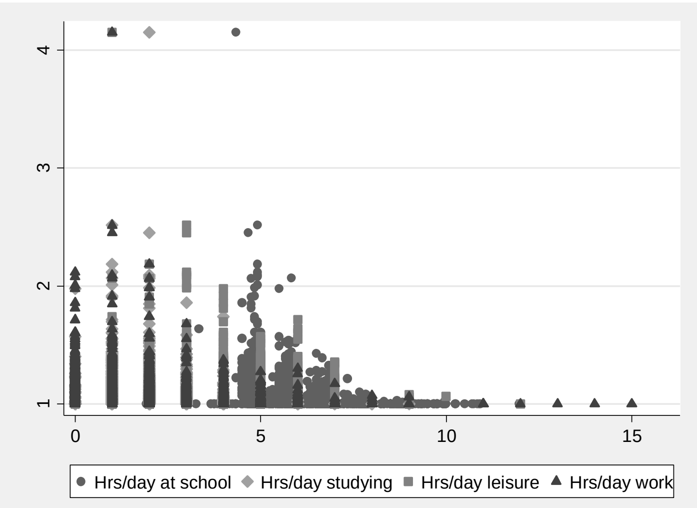
Table A10. OLS: Play time (Full sample)

	Play activities (1)	*Factor Index* (2)	*Hrs of play* (3)
Treatment Group	0.362**	0.115	0.172
	(0.127)	(0.100)	(0.130)
Public childcare (BL)	-0.044	0.068	-0.123
	(0.179)	(0.134)	(0.217)
Private childcare (BL)	-0.322	-0.173	-0.609**
	(0.208)	(0.144)	(0.157)
Informal childcare (BL)	-0.136	-0.225	-0.024
	(0.221)	(0.158)	(0.229)
Boys (=1 if male)	0.020	0.024	0.049
	(0.081)	(0.064)	(0.083)

	Play activities (1)	*Factor Index* (2)	*Hrs of play* (3)
Age (months)	0.012	-0.021	-0.019
	(0.094)	(0.072)	(0.117)
Age sq. (months)	-0.001	0.000	0.000
	(0.003)	(0.002)	(0.003)
Mother total years of education at BL	0.036**	0.021*	0.047**
	(0.010)	(0.009)	(0.011)
Employed mother at BL	0.033	0.013	-0.118
	(0.073)	(0.067)	(0.092)
Single mother at BL	-0.090	-0.009	0.008
	(0.087)	(0.065)	(0.100)
Any childcare before BL	-0.087	0.078	-0.009
	(0.119)	(0.108)	(0.121)
Grandparent in HH	-0.066	-0.117	-0.202*
	(0.090)	(0.064)	(0.099)
Wealth index[3]	0.026	0.002	0.022
	(0.025)	(0.016)	(0.023)
Number of Children aged 6 years-old or younger	-0.071	0.344**	-0.087
	(0.052)	(0.050)	(0.052)
Baseline outcome (number play activities, factor index, total hours of play)	0.179**	0.116**	0.095**
	(0.031)	(0.037)	(0.027)
Constant	0.888	-0.425	1.207
	(0.821)	(0.624)	(0.992)
R-squared	0.088	0.080	0.057
Prob>F	0.005	0.25	0.19
Observations	1,120	1,120	1,120

*p<0.05, **p<0.01, ***p<0.001 Each column represents a separate regression. Standard errors in parentheses are adjusted for clustering at municipality level.

Figure B1. Inverse Probability Weights and time inputs*



*Inverse probability weights ranged from 1 (1%) to 4.15 (99%), with an overall mean of 1.044 and standard deviation of 0.111.

Table B2. Difference in means with IPW and no weights

	IPW (1)	*No weights* (2)
PPVT score	0.451 (0.736)	0.450 (0.735)
Self-Efficacy index	0.023 (0.997)	0.021 (0.997)
Self-Esteem index	0.019 (0.979)	0.019 (0.979)

*Table reports means and standard deviations in parentheses applying the derived inverse probability weights (Column 1) and no weights (Column 2) for outcomes from the paired analytic sample (n= 5034).

Table B3. Difference in means Young Lives Unweighted Sample vs. Paired Analytic Sample

	Young Lives Unweighted Sample	*Paired Analytic Sample*	*Diff. in means*
Time inputs			
Hrs/day at school	5.478	6.385	-0.907***
Hrs/day studying outside school	1.588	1.961	-0.374***
Hrs/day in leisure activities	4.166	3.708	0.458***
Hrs/day in child work	2.682	2.180	0.502***
Child Characteristics			
Age (in months)	134.100	139.019	-4.919***
Birth order (all siblings)	2.549	2.368	0.181**
Female (prop.)	0.495	0.501	-0.006
Children attended pre-primary (prop.)	0.908	0.954	-0.046***
Language is Spanish (prop.)	0.652	0.866	-0.214***
Religion is Catholic (prop.)	0.799	0.813	-0.013
Other religion (prop.)	0.158	0.136	0.021*
Ethnicity is Mestizo (prop.)	0.890	0.923	-0.032***
Ethnicity is White (prop.)	0.061	0.056	0.005
Child is underweight (prop.)	0.188	0.064	0.125***
Household Characteristics			
Number of siblings aged 0-5 years old	0.626	0.569	0.057*
Number of siblings aged 6-12 years old	0.795	0.652	0.143***
Wealth index	0.509	0.598	-0.089***
Monthly expenditure in education items per capita	9.948	13.714	-3.766***
Monthly expenditure in food items per capita	118.309	132.692	-14.383***
Parental Characteristics			
Mom age (at birth)	26.807	26.831	-0.024
Caregiver years of education (at birth)	6.185	7.259	-1.073***
Head of household is female (prop.)	0.159	0.164	-0.005
Region Characteristics			
Child lives in Coast region (prop.)	0.291	0.358	-0.066***
Child lives in Mountain region (prop.)	0.521	0.501	0.021
Child lives in Jungle region (prop.)	0.187	0.142	0.045***
Child lives in Urban area (prop.)	0.618	0.7	-0.083***
Observations (Children)	374	1678	
Observations (Children-Data points)	1122	5034	

***p<0.01, **p<0.05, *p<0.1. Compares difference in means between paired analytic sample and the excluded observations from the Young Lives unweighted sample from Round 3 to Round 5.

Table B4. Cronbach's alpha for Self-Efficacy

Item	*Item-test correlation*	*Item-rest correlation*	*Average interitem correlation*	*Alpha*
(1) If I try hard, I can improve my situation in life	0.591	0.259	0.115	0.342
(2) Other people in my family make all the decisions about how I spend my time [recoded to positive]	0.473	0.111	0.171	0.452
(3) I have no choice about the work I do—I must do this sort of work [recoded to positive]	0.471	0.117	0.164	0.439
(4) I like to make plans for my future studies and work	0.618	0.297	0.102	0.313
(5) If I study hard at school, I will be rewarded by a better job in the future	0.624	0.308	0.098	0.303
Test scale			0.1306	0.429

Matrix Interitem correlations among items	(1)	(2)	(3)	(4)	(5)
(1)	1.000				
(2)	0.021	1.000			
(3)	0.011	0.193	1.000		
(4)	0.248	0.052	0.058	1.000	
(5)	0.309	0.043	0.024	0.311	1.000

Table B5. Cronbach's alpha for Self-Esteem

Item	*Item-test correlation*	*Item-rest correlation*	*Average interitem correlation*	*Alpha*
(1) If I try hard, I can improve my situation in life	0.703	0.461	0.192	0.488
(2) Other people in my family make all the decisions about how I spend my time [recoded to positive]	0.648	0.383	0.222	0.532
(3) I have no choice about the work I do—I must do this sort of work [recoded to positive]	0.540	0.238	0.282	0.611
(4) I like to make plans for my future studies and work	0.656	0.395	0.218	0.527
(5) If I study hard at school, I will be rewarded by a better job in the future	0.583	0.302	0.252	0.574
Test scale			0.2334	0.6036

Matrix Interitem correlations among items	(1)	(2)	(3)	(4)	(5)
(1)	1.000				
(2)	0.367	1.000			
(3)	0.223	0.106	1.000		
(4)	0.347	0.276	0.193	1.000	
(5)	0.221	0.253	0.128	0.198	1.000

Table B6. Correlation matrix for outcomes and time inputs with round

	PPVT score	*Self-Efficacy index*	*Self-Esteem index*	*Hrs/day at school*	*Hrs/day studying*	*Hrs/day in leisure*	*Hrs/day in child work*	*Round*
PPVT score	1.000							
Self-Efficacy index	0.274*	1.000						
Self-Esteem index	0.200*	0.245*	1.000					
Hrs/day at school	0.623*	0.133*	0.080*	1.000				
Hrs/day studying	0.397*	0.147*	0.0897*	0.332*	1.000			
Hrs/day in leisure	-0.116*	0.011	-0.038*	-0.291*	-0.217*	1.000		
Hrs/day in child work	0.217*	-0.124*	-0.048*	0.115*	-0.043*	-0.369*	1.000	
Round	0.819*	0.153*	0.090*	0.633*	0.316*	-0.161*	0.360*	1.000

*p<0.05. Correlation matrix for the paired analytic sample (n = 5034).

Table B7. Coefficients on Time Inputs for PPVT score

	Benchmark (CT)	*CU_{t-1}*	*CU_{t-2}*	*CVA*	*CVA-IV*
	(1)	(2)	(3)	(4)	(5)
Child is female	-0.085***	-0.085***	-0.102***	-0.065***	-0.029***
	(0.027)	(0.018)	(0.020)	(0.012)	(0.009)
Child speaks Spanish	0.100	0.186***	0.205***	0.126***	0.049
	(0.093)	(0.039)	(0.048)	(0.038)	(0.036)
Child religion: Other	0.017	0.101***	0.099***	0.043**	-0.011
	(0.032)	(0.018)	(0.022)	(0.017)	(0.016)
Child religion: None	-0.008	0.030	-0.005	-0.028	-0.051**
	(0.071)	(0.036)	(0.041)	(0.027)	(0.021)
Child is moderately underweight	-0.144**	-0.121***	-0.154***	-0.101***	-0.048**
	(0.062)	(0.041)	(0.041)	(0.022)	(0.023)
Child severely underweight	0.219	-0.196*	-0.070	0.030	0.128**
	(0.186)	(0.104)	(0.117)	(0.073)	(0.065)
Child ethnicity is White	-0.172*	-0.047*	-0.051	-0.028	-0.005
	(0.095)	(0.027)	(0.035)	(0.021)	(0.016)
Child ethnicity is Minority	0.051	0.004	-0.063	-0.093**	-0.122***
	(0.064)	(0.052)	(0.056)	(0.036)	(0.020)
Child lived at Mountain	-0.080	0.162	0.112	-0.005	-0.120
	(0.093)	(0.122)	(0.134)	(0.125)	(0.122)
Child lived at Jungle	-0.440**	-0.098	-0.179	-0.238*	-0.297**
	(0.167)	(0.123)	(0.132)	(0.127)	(0.143)
Child lived Rural area	-0.005	-0.107**	-0.071*	-0.011	0.048**
	(0.029)	(0.038)	(0.039)	(0.023)	(0.020)
Birth order: 2	0.046	-0.019	-0.013	-0.012	-0.011
	(0.041)	(0.019)	(0.025)	(0.018)	(0.014)
Birth order: 3	0.071	-0.079***	-0.091***	-0.061***	-0.030**
	(0.059)	(0.025)	(0.028)	(0.019)	(0.015)
Birth order: 4	0.083*	-0.094**	-0.086*	-0.038	0.009
	(0.048)	(0.039)	(0.045)	(0.030)	(0.020)
Birth order: 5	0.106	-0.148***	-0.180***	-0.105***	-0.030
	(0.073)	(0.045)	(0.051)	(0.033)	(0.031)
Birth order: 6	-0.060	-0.151**	-0.196***	-0.113***	-0.031
	(0.103)	(0.063)	(0.059)	(0.034)	(0.039)
Birth order: 7	0.062	-0.239**	-0.246**	-0.135	-0.026
	(0.139)	(0.088)	(0.113)	(0.084)	(0.070)
Birth order: 8	0.010	-0.165	-0.187	0.014	0.213***
	(0.133)	(0.106)	(0.131)	(0.070)	(0.045)
Birth order: 9	-0.163	-0.338***	-0.278**	-0.083	0.110
	(0.150)	(0.115)	(0.132)	(0.092)	(0.087)
Birth order: 10	0.072	-0.279	-0.333	-0.210	-0.088
	(0.077)	(0.283)	(0.347)	(0.269)	(0.190)

	Benchmark (CT)	CU_{t-1}	CU_{t-2}	*CVA*	*CVA-IV*
	(1)	(2)	(3)	(4)	(5)
Child attended pre-primary before 4 years-old	-0.010	0.096**	0.082*	0.027	-0.028
	(0.046)	(0.039)	(0.041)	(0.027)	(0.026)
Mom age at Round 1 (YL child age: 6-18 months)	0.007**	0.004**	0.006**	0.003*	-0.000
	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)
Caregiver years of education = 1	0.047	0.086*	0.055	0.015	-0.025
	(0.085)	(0.047)	(0.055)	(0.038)	(0.032)
Caregiver years of education = 2	0.207***	0.110*	0.113*	0.021	-0.070**
	(0.043)	(0.054)	(0.056)	(0.037)	(0.035)
Caregiver years of education = 3	0.141***	0.068	0.076	0.026	-0.024
	(0.035)	(0.067)	(0.080)	(0.049)	(0.027)
Caregiver years of education = 4	0.066	0.100**	0.072	0.011	-0.050
	(0.046)	(0.041)	(0.061)	(0.046)	(0.036)
Caregiver years of education = 5	0.096***	0.069**	0.047	0.002	-0.043
	(0.028)	(0.033)	(0.049)	(0.040)	(0.038)
Caregiver years of education = 6	0.191***	0.134***	0.122**	0.040	-0.041*
	(0.044)	(0.041)	(0.047)	(0.032)	(0.023)
Caregiver years of education = 7	0.331***	0.143	0.109	0.014	-0.081
	(0.074)	(0.089)	(0.102)	(0.072)	(0.056)
Caregiver years of education = 8	0.285**	0.173***	0.140**	0.039	-0.060**
	(0.118)	(0.051)	(0.062)	(0.041)	(0.028)
Caregiver years of education = 9	0.240***	0.136**	0.092	0.018	-0.055*
	(0.072)	(0.059)	(0.069)	(0.044)	(0.031)
Caregiver years of education = 10	0.233**	0.157*	0.147	0.064	-0.018
	(0.083)	(0.083)	(0.100)	(0.065)	(0.036)
Caregiver years of education = 11	0.358***	0.214***	0.185***	0.063	-0.058**
	(0.081)	(0.051)	(0.059)	(0.039)	(0.028)
Caregiver years of education = 12	0.666***	0.320***	0.276***	0.109**	-0.057**
	(0.081)	(0.061)	(0.070)	(0.046)	(0.024)
Caregiver years of education = 13	0.402***	0.295***	0.279***	0.109**	-0.060*
	(0.118)	(0.059)	(0.070)	(0.047)	(0.034)
Caregiver years of education = 14	0.618***	0.434***	0.381***	0.137***	-0.105***
	(0.088)	(0.048)	(0.060)	(0.042)	(0.030)
Caregiver years of education = 15	0.819***	0.435***	0.340***	0.102*	-0.134***
	(0.107)	(0.060)	(0.069)	(0.053)	(0.046)
Head of household is female	-0.101	0.024	0.013	0.004	-0.005
	(0.062)	(0.019)	(0.021)	(0.016)	(0.016)
Child's age (in months)	0.013***	0.014***	0.010***	0.002	-0.005***
	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
Number of males aged 0-5	-0.068***	-0.016	0.005	0.005	0.005
	(0.022)	(0.017)	(0.024)	(0.016)	(0.012)
Number of females aged 0-5	-0.024	-0.015	0.005	-0.005	-0.014
	(0.028)	(0.014)	(0.015)	(0.013)	(0.016)
Number of males aged 6-12	-0.027	0.009	0.013	0.012	0.012
	(0.025)	(0.011)	(0.012)	(0.009)	(0.009)
Number of females aged 6-12	-0.062***	-0.007	-0.003	0.003	0.008
	(0.018)	(0.013)	(0.018)	(0.013)	(0.011)
Wealth index	0.217	0.621***	0.540***	0.275***	0.014
	(0.200)	(0.088)	(0.092)	(0.073)	(0.066)
Monthly expenditure in education items per capita	0.009***	0.001**	0.001**	0.000	-0.000*
	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)
Monthly expenditure in food items per capita	-0.001***	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-2.589***	-3.159***	-2.798***	-0.890**	0.996***
	(0.372)	(0.238)	(0.455)	(0.373)	(0.352)

***p<0.01, **p<0.05, *p<0.1. Clustered robust standard errors in parentheses at the village level. Each column presents a separate regression, using inverse probability weights.

Table B8. Coefficients on Time Inputs for Self-Efficacy Index (all controls)

	Benchmark (CT) (1)	CU_{t-1} (2)	CU_{t-2} (3)	*CVA* (4)	*CVA-IV* (5)
Child is female	0.165***	0.166***	0.275***	0.250***	0.023
	(0.035)	(0.034)	(0.066)	(0.066)	(0.403)
Child speaks Spanish	0.122**	0.103**	-0.041	-0.071	-0.341
	(0.046)	(0.048)	(0.069)	(0.070)	(0.537)
Child religion: Other	0.051	0.071*	0.049	0.027	-0.162
	(0.040)	(0.040)	(0.064)	(0.062)	(0.335)
Child religion: None	-0.017	-0.024	-0.025	-0.053	-0.303
	(0.074)	(0.073)	(0.143)	(0.143)	(0.503)
Child is moderately underweight	-0.055	-0.062	-0.010	0.022	0.299
	(0.057)	(0.062)	(0.127)	(0.124)	(0.509)
Child severely underweight	-0.114	-0.122	-0.044	-0.004	0.342
	(0.156)	(0.155)	(0.195)	(0.196)	(0.715)
Child ethnicity is White	-0.022	-0.025	-0.073	-0.069	-0.036
	(0.083)	(0.084)	(0.092)	(0.088)	(0.165)
Child ethnicity is Minority	-0.143*	-0.153**	-0.068	-0.033	0.278
	(0.069)	(0.065)	(0.195)	(0.201)	(0.628)
Child lived at Mountain	0.060	0.066	0.067	0.083	0.224
	(0.594)	(0.594)	(0.625)	(0.607)	(0.671)
Child lived at Jungle	0.057	0.059	0.125	0.132	0.195
	(0.459)	(0.466)	(0.531)	(0.473)	(0.882)
Child lived Rural area	-0.163**	-0.162**	-0.069	-0.046	0.155
	(0.059)	(0.059)	(0.106)	(0.104)	(0.423)
Birth order: 2	-0.027	-0.027	0.135	0.147*	0.249
	(0.042)	(0.043)	(0.086)	(0.084)	(0.192)
Birth order: 3	-0.057	-0.068	-0.105	-0.100	-0.056
	(0.058)	(0.060)	(0.098)	(0.096)	(0.145)
Birth order: 4	-0.054	-0.070	-0.061	-0.050	0.045
	(0.084)	(0.085)	(0.107)	(0.096)	(0.211)
Birth order: 5	-0.051	-0.059	0.116	0.134	0.290
	(0.082)	(0.082)	(0.147)	(0.141)	(0.308)
Birth order: 6	0.022	0.000	0.183	0.196	0.311
	(0.086)	(0.088)	(0.121)	(0.117)	(0.264)
Birth order: 7	0.018	0.011	0.155	0.185	0.450
	(0.145)	(0.149)	(0.202)	(0.204)	(0.559)
Birth order: 8	-0.075	-0.081	-0.228	-0.234	-0.281
	(0.124)	(0.139)	(0.151)	(0.160)	(0.674)
Birth order: 9	-0.061	-0.045	-0.402	-0.411	-0.489
	(0.385)	(0.380)	(0.355)	(0.274)	(0.836)
Birth order: 10	0.116	0.140	0.265	0.251	0.125
	(0.368)	(0.366)	(0.508)	(0.441)	(0.403)
Child attended pre-primary before 4 years-old	-0.008	-0.007	0.065	0.075	0.166
	(0.060)	(0.066)	(0.126)	(0.124)	(0.272)
Mom age at Round 1 (YL child age: 6-18 months)	0.010**	0.010**	0.010**	0.008*	-0.010
	(0.004)	(0.004)	(0.005)	(0.004)	(0.030)
Caregiver years of education = 1	0.138*	0.118	0.162	0.144	-0.012
	(0.076)	(0.077)	(0.189)	(0.171)	(0.243)
Caregiver years of education = 2	-0.003	-0.010	0.092	0.143	0.595
	(0.081)	(0.082)	(0.170)	(0.165)	(0.825)
Caregiver years of education = 3	0.155*	0.149*	0.207	0.225*	0.385
	(0.075)	(0.076)	(0.125)	(0.125)	(0.413)
Caregiver years of education = 4	0.173**	0.172**	0.159	0.124	-0.186
	(0.065)	(0.068)	(0.144)	(0.146)	(0.569)
Caregiver years of education = 5	0.163**	0.156**	0.232	0.222	0.136
	(0.064)	(0.064)	(0.152)	(0.154)	(0.295)
Caregiver years of education = 6	0.131***	0.128**	0.250*	0.245*	0.202
	(0.042)	(0.045)	(0.134)	(0.136)	(0.229)

	Benchmark (CT)	CU_{t-1}	CU_{t-2}	CVA	CVA-IV
	(1)	(2)	(3)	(4)	(5)
Caregiver years of education = 7	0.168 (0.100)	0.168 (0.098)	0.365* (0.204)	0.330 (0.204)	0.020 (0.591)
Caregiver years of education = 8	0.081 (0.091)	0.074 (0.090)	0.184 (0.161)	0.182 (0.163)	0.160 (0.318)
Caregiver years of education = 9	0.127 (0.075)	0.110 (0.079)	0.161 (0.171)	0.174 (0.180)	0.291 (0.398)
Caregiver years of education = 10	0.306*** (0.103)	0.290** (0.105)	0.479** (0.171)	0.444** (0.169)	0.135 (0.544)
Caregiver years of education = 11	0.230*** (0.057)	0.213*** (0.060)	0.283* (0.144)	0.250 (0.149)	-0.044 (0.557)
Caregiver years of education = 12	0.248*** (0.063)	0.224*** (0.063)	0.227 (0.165)	0.209 (0.167)	0.048 (0.364)
Caregiver years of education = 13	0.187* (0.090)	0.176* (0.087)	0.344* (0.169)	0.324* (0.169)	0.144 (0.376)
Caregiver years of education = 14	0.493*** (0.100)	0.472*** (0.099)	0.698*** (0.181)	0.654*** (0.178)	0.272 (0.767)
Caregiver years of education = 15	0.140 (0.113)	0.114 (0.114)	0.259 (0.223)	0.223 (0.226)	-0.099 (0.570)
Head of household is female	0.079 (0.051)	0.083 (0.052)	0.065 (0.067)	0.052 (0.067)	-0.056 (0.230)
Child's age (in months)	0.012*** (0.003)	0.012*** (0.004)	0.011 (0.006)	0.007 (0.006)	-0.023 (0.051)
Number of males aged 0-5	0.047* (0.024)	0.054** (0.025)	0.083* (0.047)	0.077 (0.046)	0.021 (0.124)
Number of females aged 0-5	0.020 (0.025)	0.025 (0.026)	0.108 (0.066)	0.120* (0.064)	0.229 (0.204)
Number of males aged 6-12	-0.023 (0.025)	-0.021 (0.025)	0.007 (0.043)	0.011 (0.039)	0.049 (0.095)
Number of females aged 6-12	-0.001 (0.024)	0.005 (0.024)	0.005 (0.047)	0.001 (0.050)	-0.036 (0.119)
Wealth index	0.304** (0.134)	0.260* (0.136)	0.381** (0.181)	0.348* (0.170)	0.056 (0.661)
Monthly expenditure in education items per capita	0.001 (0.001)	0.001 (0.001)	0.002* (0.001)	0.002* (0.001)	0.002 (0.002)
Monthly expenditure in food items per capita	0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.000 (0.001)
Constant	-1.892*** (0.612)	-1.918*** (0.618)	-3.060** (1.341)	-2.207 (1.340)	5.287 (12.392)

***p<0.01, **p<0.05, *p<0.1. Clustered robust standard errors in parentheses at the village level. Each column presents a separate regression, using inverse probability weights.

Table B9. Coefficients on Time Inputs for Self-Esteem Index (all controls)

	Benchmark (CT)	CU_{t-1}	CU_{t-2}	CVA	CVA-IV
	(1)	(2)	(3)	(4)	(5)
Child is female	0.022 (0.025)	0.026 (0.026)	0.018 (0.041)	0.016 (0.041)	0.018 (0.038)
Child speaks Spanish	0.136** (0.052)	0.160*** (0.052)	0.051 (0.092)	0.020 (0.092)	0.055 (0.129)
Child religion: Other	0.000 (0.042)	0.002 (0.041)	-0.010 (0.075)	0.006 (0.079)	-0.012 (0.102)
Child religion: None	-0.119** (0.053)	-0.109** (0.052)	-0.116 (0.075)	-0.100 (0.077)	-0.117 (0.106)
Child is moderately underweight	-0.118 (0.100)	-0.131 (0.101)	-0.284* (0.146)	-0.241 (0.149)	-0.289 (0.277)
Child severely underweight	-0.022 (0.065)	-0.013 (0.057)	0.085 (0.124)	0.175 (0.123)	0.075 (0.382)

	Benchmark (CT) (1)	*CU_{t-1}* (2)	*CU_{t-2}* (3)	*CVA* (4)	*CVA-IV* (5)
Child ethnicity is White	-0.013 (0.066)	-0.019 (0.067)	0.123 (0.098)	0.134 (0.099)	0.121 (0.104)
Child ethnicity is Minority	0.218*** (0.066)	0.224*** (0.068)	0.087 (0.149)	0.012 (0.140)	0.095 (0.352)
Child lived at Mountain	0.278 (0.220)	0.288 (0.226)	0.344 (0.322)	0.343 (0.280)	0.344 (0.311)
Child lived at Jungle	-0.145 (0.361)	-0.136 (0.361)	-0.136 (0.398)	-0.092 (0.349)	-0.141 (0.441)
Child lived Rural area	-0.112* (0.058)	-0.113* (0.057)	-0.031 (0.097)	-0.023 (0.103)	-0.032 (0.105)
Birth order: 2	-0.111*** (0.037)	-0.108** (0.039)	-0.059 (0.054)	-0.034 (0.053)	-0.061 (0.129)
Birth order: 3	-0.165*** (0.052)	-0.160*** (0.054)	-0.113 (0.074)	-0.092 (0.070)	-0.115 (0.109)
Birth order: 4	-0.203** (0.088)	-0.200** (0.087)	-0.035 (0.103)	0.004 (0.095)	-0.039 (0.202)
Birth order: 5	-0.231*** (0.069)	-0.217*** (0.070)	-0.097 (0.086)	-0.061 (0.076)	-0.101 (0.142)
Birth order: 6	-0.193 (0.135)	-0.175 (0.133)	-0.225** (0.104)	-0.205** (0.091)	-0.227* (0.138)
Birth order: 7	-0.087 (0.133)	-0.054 (0.131)	0.088 (0.187)	0.082 (0.187)	0.089 (0.185)
Birth order: 8	-0.465** (0.198)	-0.458** (0.206)	-0.211 (0.263)	-0.126 (0.303)	-0.221 (0.450)
Birth order: 9	-0.449* (0.240)	-0.433* (0.250)	0.093 (0.230)	0.155 (0.237)	0.086 (0.338)
Birth order: 10	0.117 (0.318)	0.173 (0.298)	-0.632** (0.231)	-0.784*** (0.170)	-0.616 (0.777)
Child attended pre-primary before 4 years-old	0.051 (0.081)	0.014 (0.082)	-0.068 (0.136)	-0.089 (0.128)	-0.066 (0.179)
Mom age at Round 1 (YL child age: 6-18 months)	0.004 (0.003)	0.004 (0.003)	-0.001 (0.004)	-0.002 (0.004)	-0.001 (0.005)
Caregiver years of education = 1	0.083 (0.067)	0.076 (0.066)	0.148 (0.160)	0.135 (0.163)	0.150 (0.158)
Caregiver years of education = 2	0.012 (0.086)	0.016 (0.082)	0.094 (0.128)	0.117 (0.122)	0.091 (0.129)
Caregiver years of education = 3	-0.019 (0.063)	-0.011 (0.057)	0.067 (0.080)	0.118 (0.087)	0.062 (0.254)
Caregiver years of education = 4	-0.022 (0.079)	-0.017 (0.076)	-0.039 (0.126)	-0.020 (0.127)	-0.041 (0.164)
Caregiver years of education = 5	0.047 (0.081)	0.047 (0.082)	-0.016 (0.101)	0.009 (0.099)	-0.019 (0.169)
Caregiver years of education = 6	0.022 (0.057)	0.017 (0.057)	0.040 (0.070)	0.061 (0.074)	0.038 (0.105)
Caregiver years of education = 7	-0.100 (0.152)	-0.098 (0.153)	0.006 (0.244)	0.048 (0.216)	0.001 (0.300)
Caregiver years of education = 8	0.055 (0.094)	0.050 (0.093)	0.060 (0.170)	0.071 (0.169)	0.059 (0.174)
Caregiver years of education = 9	0.142* (0.076)	0.129* (0.073)	0.149* (0.082)	0.176** (0.084)	0.146 (0.135)
Caregiver years of education = 10	-0.040 (0.073)	-0.045 (0.072)	0.012 (0.120)	0.066 (0.131)	0.007 (0.276)
Caregiver years of education = 11	0.076 (0.070)	0.069 (0.070)	0.122 (0.097)	0.145 (0.101)	0.120 (0.129)
Caregiver years of education = 12	0.051 (0.100)	0.038 (0.100)	0.139 (0.169)	0.146 (0.170)	0.138 (0.162)
Caregiver years of education = 13	0.036 (0.087)	0.033 (0.084)	0.062 (0.150)	0.079 (0.152)	0.061 (0.169)
Caregiver years of education = 14	0.150 (0.102)	0.144 (0.102)	-0.191 (0.152)	-0.161 (0.147)	-0.194 (0.187)

	Benchmark (CT)	*CU_{t-1}*	*CU_{t-2}*	*CVA*	*CVA-IV*
	(1)	(2)	(3)	(4)	(5)
Caregiver years of education = 15	0.133	0.119	0.291	0.313	0.288
	(0.136)	(0.134)	(0.211)	(0.213)	(0.233)
Head of household is female	0.014	0.010	-0.014	-0.025	-0.013
	(0.046)	(0.048)	(0.076)	(0.070)	(0.076)
Child's age (in months)	-0.001	-0.003	-0.009	-0.011*	-0.009
	(0.004)	(0.004)	(0.006)	(0.006)	(0.011)
Number of males aged 0-5	-0.042	-0.038	-0.074	-0.078	-0.074
	(0.034)	(0.034)	(0.051)	(0.051)	(0.048)
Number of females aged 0-5	-0.081***	-0.080***	-0.043	-0.028	-0.045
	(0.026)	(0.027)	(0.063)	(0.064)	(0.071)
Number of males aged 6-12	-0.007	-0.002	-0.000	-0.010	0.000
	(0.027)	(0.026)	(0.046)	(0.046)	(0.059)
Number of females aged 6-12	-0.039	-0.037	-0.078*	-0.077*	-0.078**
	(0.029)	(0.030)	(0.039)	(0.040)	(0.037)
Wealth index	0.346**	0.300*	0.315	0.233	0.323
	(0.154)	(0.154)	(0.202)	(0.192)	(0.321)
Monthly expenditure in education items per capita	0.001	0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Monthly expenditure in food items per capita	0.000**	0.000**	0.001**	0.000*	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-1.089**	-0.984**	0.756	1.259	0.703
	(0.427)	(0.410)	(1.140)	(1.089)	(2.534)

***p<0.01, **p<0.05, *p<0.1. Clustered robust standard errors in parentheses at the village level. Each column presents a separate regression, using inverse probability weights.

Table B10. First-stage results of main results

CVA-IV	*PPVT*	*Self-Efficacy*	*Self-Esteem*
	(1)	(2)	(3)
Hrs/day at school	0.019**	0.005	0.003
	(0.006)	(0.023)	(0.019)
Hrs/day at school$_{t-1}$	0.024**	0.048	0.010
	(0.010)	(0.038)	(0.035)
Hrs/day at school$_{t-2}$	-0.005	0.020	0.041
	(0.008)	(0.038)	(0.042)
Hrs/day studying outside school	0.014**	-0.001	0.034
	(0.006)	(0.038)	(0.024)
Hrs/day studying outside school$_{t-1}$	0.027***	0.031	-0.022
	(0.008)	(0.027)	(0.029)
Hrs/day studying outside school$_{t-2}$	0.029**	0.070	0.055
	(0.009)	(0.037)	(0.036)
Hrs/day in leisure activities	0.011*	-0.007	-0.009
	(0.005)	(0.018)	(0.014)
Hrs/day in leisure activities$_{t-1}$	0.013*	0.008	-0.047
	(0.006)	(0.022)	(0.027)
Hrs/day in leisure activities$_{t-2}$	0.006	0.044	0.004
	(0.006)	(0.024)	(0.020)
Hrs/day in child work	0.001	0.014	0.012
	(0.004)	(0.019)	(0.014)
Hrs/day in child work$_{t-1}$	0.008	-0.006	0.003
	(0.007)	(0.016)	(0.019)
Hrs/day in child work$_{t-2}$	-0.030***	-0.010	-0.017
	(0.006)	(0.023)	(0.023)
Instruments: (1) PPVT score$_{t-2;}$ (2) Self-Efficacy score$_{t-2}$; (3) Self-Esteem$_{t-2}$;	0.419***	0.023	0.031
	(0.029)	(0.032)	(0.025)
R-squared	0.718	0.138	0.099
Observations	3,044	1,626	1626

***p<0.01, **p<0.05, *p<0.1. Clustered robust standard errors in parentheses at the village level. Each column presents a separate regression, using inverse probability weights. Controls include time-invariant predictors (child's sex, birth order, child's language, ethnicity, region and area of residence at Round 1, religion, whether the child was severely or moderately underweight at Round 1, whether the child attended pre-primary education before aged 4, mother's age, main caregiver years of education; and time variant predictors (child's age in months, number of siblings living in household aged 0 to 12, a household wealth index, level of food and education expenditure per capita (in *Soles*), if family head is female) and village fixed effects. Reference categories: (Child's sex) Female, (Language) Other, (Birth order) First-born, (Underweight) Not underweighted (Ethnicity) Mestizo (includes Native of the Amazon, Negro & Asiatic), (Religion) Catholic, (Language) Other (Area) Urban, (Region) Coast.

Table B11. Alternative instruments: First-stage results for PPVT score

CVA-IV	*Instr: $PPVT_{t-3}$*	*Instr: Self-$Efficacy_{t-1}$*	*Instr: Self-$Esteem_{t-1}$*	*Instr: Self-$Efficacy_{t-2}$*	*Instr: Self-$Esteem_{t-2}$*	*Instr: Self-$Efficacy_{t-2}$, Self-$Esteem_{t-2}$ & $PPVT_{t-2}$*
	(1)	(2)	(3)	(4)	(5)	(6)
Hrs/day at school	0.018*	0.028***	0.031***	0.027***	0.027***	0.020***
	(0.010)	(0.006)	(0.007)	(0.008)	(0.008)	(0.008)
Hrs/day at school$_{t-1}$	0.025	0.031**	0.032**	0.051**	0.050**	0.026*
	(0.019)	(0.013)	(0.013)	(0.020)	(0.020)	(0.015)
Hrs/day at school$_{t-2}$	0.016	0.008	0.008	0.011	0.009	0.008
	(0.014)	(0.007)	(0.007)	(0.016)	(0.016)	(0.013)
Hrs/day studying outside school	0.019	0.026***	0.026***	0.031**	0.032**	0.018
	(0.013)	(0.007)	(0.007)	(0.014)	(0.014)	(0.015)
Hrs/day studying outside school$_{t-1}$	0.034**	0.027***	0.027***	0.041***	0.042***	0.029***
	(0.012)	(0.009)	(0.009)	(0.011)	(0.011)	(0.008)
Hrs/day studying outside school$_{t-2}$	0.045***	0.043***	0.043***	0.046***	0.044***	0.036**
	(0.013)	(0.010)	(0.010)	(0.016)	(0.016)	(0.014)
Hrs/day in leisure activities	0.003	0.010	0.014**	0.005	0.005	0.006
	(0.011)	(0.006)	(0.007)	(0.011)	(0.011)	(0.010)
Hrs/day in leisure activities$_{t-1}$	0.014	0.014**	0.014**	0.010	0.010	0.005
	(0.009)	(0.007)	(0.007)	(0.010)	(0.010)	(0.008)
Hrs/day in leisure activities$_{t-2}$	0.023**	0.001	0.001	0.025***	0.025***	0.016*
	(0.008)	(0.006)	(0.006)	(0.009)	(0.008)	(0.009)
Hrs/day in child work	-0.001	-0.001	0.000	0.001	0.001	0.004
	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Hrs/day in child work$_{t-1}$	0.005	0.005	0.005	0.004	0.004	0.005
	(0.009)	(0.007)	(0.007)	(0.009)	(0.010)	(0.007)
Hrs/day in child work$_{t-2}$	-0.013*	-0.026***	-0.026***	-0.018***	-0.018**	-0.021***
	(0.007)	(0.005)	(0.004)	(0.007)	(0.007)	(0.009)
Instruments: (1) $PPVT_{t-3;}$ (2) Self-$Efficacy_{t-1}$; (3) Self-$Esteem_{t-1}$; (4) Self-$Efficacy_{t-2}$; (5) Self-$Esteem_{t-2}$; (6) $PPVT_{t-2}$	0.419***	0.019**	0.023***	-0.002	0.039***	0.464***
	(0.025)	(0.007)	(0.007)	(0.012)	(0.012)	(0.037)
Instruments: (6) Self-$Efficacy_{t-2}$						-0.007
						(0.011)
Instruments: (6) Self-$Esteem_{t-2}$;						0.019*
						(0.011)
R-squared	0.543	0.666	0.664	0.469	0.473	0.583
Observations	1510	3,039	3,040	1,553	1,553	1,553

***p<0.01, **p<0.05, *p<0.1. Clustered robust standard errors in parentheses at the village level. Each column presents a separate regression, using inverse probability weights. Controls include time-invariant predictors (child's sex, birth order, child's language, ethnicity, region and area of residence at Round 1, religion, whether the child was severely or moderately underweight at Round 1, whether the child attended pre-primary education before aged 4, mother's age, main caregiver years of education; and time variant predictors (child's age in months, number of siblings living in household aged 0 to 12, a household wealth index, level of food and education expenditure per capita (in *Soles*), if family head is female) and village fixed effects. Reference categories: (Child's sex) Female, (Language) Other, (Birth order) First-born, (Underweight) Not underweighted (Ethnicity) Mestizo (includes Native of the Amazon, Negro & Asiatic), (Religion) Catholic, (Language) Other (Area) Urban, (Region) Coast.

Table B12. Alternative instruments: First-stage results for Self-Efficacy

CVA-IV	*Instr: $PPVT_{t-1}$*	*Instr: $PPVT_{t-2}$*	*Instr: Self-$Esteem_{t-1}$*	*Instr: Self-$Esteem_{t-2}$*	*Instr: Self-$Esteem_{t-2}$ & $PPVT_{t-2}$*	*Instr: Self-$Efficacy_{t-2,}$ Self-$Esteem_{t-2}$ & $PPVT_{t-2}$*
	(1)	(2)	(3)	(4)	(5)	(6)
Hrs/day at school	0.001	0.011	0.006	0.007	0.011	0.009
	(0.023)	(0.022)	(0.023)	(0.023)	(0.022)	(0.022)
Hrs/day at $school_{t-1}$	0.041	0.041	0.046	0.048	0.040	0.040
	(0.038)	(0.039)	(0.038)	(0.038)	(0.039)	(0.040)
Hrs/day at $school_{t-2}$	0.020	0.008	0.012	0.020	0.016	0.016
	(0.036)	(0.007)	(0.035)	(0.038)	(0.038)	(0.038)
Hrs/day studying outside school	-0.009	0.003	-0.007	-0.001	0.003	0.002
	(0.038)	(0.040)	(0.036)	(0.038)	(0.014)	(0.039)
Hrs/day studying outside $school_{t-1}$	0.025	0.028	0.035	0.030	0.028	0.028
	(0.029)	(0.031)	(0.028)	(0.027)	(0.030)	(0.030)
Hrs/day studying outside $school_{t-2}$	0.059	0.056	0.060	0.070	0.056	0.056
	(0.039)	(0.042)	(0.041)	(0.038)	(0.042)	(0.041)
Hrs/day in leisure activities	-0.010	-0.004	-0.005	-0.007	-0.004	-0.004
	(0.017)	(0.018)	(0.019)	(0.018)	(0.018)	(0.018)
Hrs/day in leisure $activities_{t-1}$	0.006	0.003	0.016	0.007	0.003	0.004
	(0.021)	(0.021)	(0.022)	(0.022)	(0.021)	(0.022)
Hrs/day in leisure $activities_{t-2}$	0.041*	0.034	0.043	0.044	0.034	0.034
	(0.023)	(0.023)	(0.025)	(0.023)	(0.023)	(0.023)
Hrs/day in child work	0.012	0.023	0.012	0.014	0.023	0.023
	(0.019)	(0.017)	(0.018)	(0.019)	(0.017)	(0.018)
Hrs/day in child $work_{t-1}$	-0.005	-0.003	-0.006	-0.006	-0.003	-0.004
	(0.016)	(0.017)	(0.016)	(0.016)	(0.017)	(0.017)
Hrs/day in child $work_{t-2}$	-0.007	-0.018	-0.008	-0.012	-0.018	-0.016
	(0.023)	(0.024)	(0.025)	(0.023)	(0.024)	(0.025)
Instr: (1) $PPVT_{t-1}$; (2) $PPVT_{t-2}$; (3) Self-$Esteem_{t-1}$; (4) Self-$Esteem_{t-2}$; (5) & (6) $PPVT_{t-2}$	0.210***	0.129*	0.184	-0.002	0.130*	0.130*
	(0.051)	(0.069)	(0.026)	(0.024)	(0.067)	(0.067)
Instr: (5) & (6) Self-$Efficacy_{t-2}$					-0.003	0.023
					(0.024)	(0.036)
Instr: (6) Self-$Esteem_{t-2}$						-0.006
						(0.024)
R-squared	0.146	0.143	0.137	0.137	0.147	0.143
Observations	1620	1555	1,626	1,626	1,555	1,555

***p<0.01, **p<0.05, *p<0.1. Clustered robust standard errors in parentheses at the village level. Each column presents a separate regression, using inverse probability weights. Controls include time-invariant predictors (child's sex, birth order, child's language, ethnicity, region and area of residence at Round 1, religion, whether the child was severely or moderately underweight at Round 1, whether the child attended pre-primary education before aged 4, mother's age, main caregiver years of education; and time variant predictors (child's age in months, number of siblings living in household aged 0 to 12, a household wealth index, level of food and education expenditure per capita (in *Soles*), if family head is female) and village fixed effects. Reference categories: (Child's sex) Female, (Language) Other, (Birth order) First-born, (Underweight) Not underweighted (Ethnicity) Mestizo (includes Native of the Amazon, Negro & Asiatic), (Religion) Catholic, (Language) Other (Area) Urban, (Region) Coast.

Table B13. Alternative instruments: First-stage results for Self-Esteem

CVA-IV	*Instr: $PPVT_{t-1}$* (1)	*Instr: $PPVT_{t-2}$* (2)	*Instr: Self-$Efficacy_{t-1}$* (3)	*Instr: Self-$Efficacy_{t-2}$* (4)	*Instr: Self-$Efficacy_{t-2}$ & $PPVT_{t-2}$* (5)	*Instr: Self-$Efficacy_{t-2}$, Self-$Esteem_{t-2}$ & $PPVT_{t-2}$* (6)
Hrs/day at school	0.004	0.006	0.002	0.002	0.005	0.005
	(0.053)	(0.021)	(0.019)	(0.020)	(0.022)	(0.022)
Hrs/day at $school_{t-1}$	0.006	0.009	0.001	0.010	0.008	0.008
	(0.034)	(0.038)	(0.035)	(0.035)	(0.038)	(0.038)
Hrs/day at $school_{t-2}$	0.043	0.030	0.012	0.043	0.030	0.028
	(0.042)	(0.042)	(0.035)	(0.041)	(0.042)	(0.042)
Hrs/day studying outside school	0.032	0.042*	0.033	0.032	0.042	0.043
	(0.024)	(0.023)	(0.022)	(0.025)	(0.023)	(0.023)
Hrs/day studying outside $school_{t-1}$	-0.022	-0.027	-0.029	-0.023	-0.027	-0.025
	(0.030)	(0.030)	(0.030)	(0.029)	(0.030)	(0.030)
Hrs/day studying outside $school_{t-2}$	0.053	0.054	0.060	0.055	0.053	0.052
	(0.036)	(0.037)	(0.041)	(0.036)	(0.037)	(0.037)
Hrs/day in leisure activities	-0.009	-0.004	-0.008	-0.010	-0.004	-0.005
	(0.014)	(0.014)	(0.015)	(0.014)	(0.014)	(0.014)
Hrs/day in leisure $activities_{t-1}$	-0.049*	-0.047*	-0.049*	-0.047*	-0.047*	-0.046*
	(0.027)	(0.029)	(0.027)	(0.027)	(0.028)	(0.028)
Hrs/day in leisure $activities_{t-2}$	0.002	0.002	0.043	0.004	0.002	0.002
	(0.020)	(0.022)	(0.025)	(0.020)	(0.021)	(0.021)
Hrs/day in child work	0.011	0.021	0.009	0.012	0.020	0.020
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Hrs/day in child $work_{t-1}$	0.003	0.003	0.004	0.002	0.002	0.002
	(0.019)	(0.020)	(0.019)	(0.019)	(0.020)	(0.020)
Hrs/day in child $work_{t-2}$	-0.018	-0.017	-0.015	-0.016	-0.016	-0.015
	(0.024)	(0.027)	(0.026)	(0.024)	(0.027)	(0.026)
Instr: (1) $PPVT_{t-1}$; (2) $PPVT_{t-2}$; (3) Self-$Esteem_{t-1}$; (4) Self-$Esteem_{t-2}$; (5) & (6) $PPVT_{t-2}$	0.016	-0.036	0.190***	0.030	-0.037	-0.045
	(0.053)	(0.064)	(0.028)	(0.030)	(0.064)	(0.064)
Instr: (5) & (6) Self-$Efficacy_{t-2}$					0.028	0.023
					(0.032)	(0.032)
Instr: (6) Self-$Esteem_{t-2}$						0.036
						(0.025)
R-squared	0.099	0.099	0.130	0.099	0.100	0.101
Observations	1,620	1,555	1,626	1,626	1,555	1,555

***p<0.01, **p<0.05, *p<0.1. Clustered robust standard errors in parentheses at the village level. Each column presents a separate regression, using inverse probability weights. Controls include time-invariant predictors (child's sex, birth order, child's language, ethnicity, region and area of residence at Round 1, religion, whether the child was severely or moderately underweight at Round 1, whether the child attended pre-primary education before aged 4, mother's age, main caregiver years of education; and time variant predictors (child's age in months, number of siblings living in household aged 0 to 12, a household wealth index, level of food and education expenditure per capita (in *Soles*), if family head is female) and village fixed effects. Reference categories: (Child's sex) Female, (Language) Other, (Birth order) First-born, (Underweight) Not underweighted (Ethnicity) Mestizo (includes Native of the Amazon, Negro & Asiatic), (Religion) Catholic, (Language) Other (Area) Urban, (Region) Coast.

Table B14. Alternative instruments: Time Inputs for PPVT score

CVA-IV	Instr: $PPVT_{t-3}$ (1)	Instr: Self-$Efficacy_{t-1}$ (2)	Instr: Self-$Esteem_{t-1}$ (3)	Instr: Self-$Efficacy_{t-2}$ (4)	Instr: Self-$Esteem_{t-2}$ (5)	Instr: Self-$Efficacy_{t-2,}$ Self-$Esteem_{t-2}$ & $PPVT_{t-2}$ (6)
Education Time Inputs						
Hrs/day at school	-0.002	-0.003	0.006	0.250	-0.012	-0.005
	(0.010)	(0.016)	(0.013)	(1.103)	(0.012)	(0.009)
Hrs/day at $school_{t-1}$	-0.001	-0.013	-0.002	0.475	-0.016	-0.003
	(0.020)	(0.016)	(0.011)	(2.181)	(0.024)	(0.020)
Hrs/day at $school_{t-2}$	-0.036***	0.008	0.011*	0.069	-0.040***	-0.037***
	(0.011)	(0.009)	(0.006)	(0.519)	(0.012)	(0.011)
Hrs/day studying outside school	0.002	0.002	0.011	0.290	-0.010	-0.002
	(0.012)	(0.016)	(0.009)	(1.329)	(0.017)	(0.013)
Hrs/day studying outside $school_{t-1}$	0.008	0.008	0.017*	0.390	-0.004	0.006
	(0.008)	(0.016)	(0.010)	(1.758)	(0.019)	(0.008)
Hrs/day studying outside $school_{t-2}$	-0.006	-0.014	0.001	0.425	-0.020	-0.008
	(0.011)	(0.030)	(0.021)	(1.996)	(0.018)	(0.013)
Leisure Time Inputs						
Hrs/day in leisure activities	-0.015	-0.012	-0.009	0.032	-0.020**	-0.019**
	(0.009)	(0.008)	(0.007)	(0.220)	(0.010)	(0.009)
Hrs/day in leisure $activities_{t-1}$	-0.014*	-0.005	-0.000	0.079	-0.016*	-0.014*
	(0.008)	(0.008)	(0.005)	(0.452)	(0.009)	(0.008)
Hrs/day in leisure $activities_{t-2}$	-0.007	0.010	0.011*	0.226	-0.016	-0.009
	(0.006)	(0.007)	(0.006)	(1.079)	(0.011)	(0.007)
Child work Time Inputs						
Hrs/day in child work	-0.009	-0.002	-0.002	-0.003	-0.011*	-0.011*
	(0.006)	(0.004)	(0.003)	(0.053)	(0.006)	(0.006)
Hrs/day in child $work_{t-1}$	-0.002	-0.010	-0.008	0.036	-0.003	-0.002
	(0.004)	(0.008)	(0.005)	(0.211)	(0.005)	(0.004)
Hrs/day in child $work_{t-2}$	-0.013	0.011	0.002	-0.186	-0.009	-0.013
	(0.009)	(0.014)	(0.011)	(0.757)	(0.012)	(0.009)
PPVT $score_{t-1}$	0.899***	1.171**	0.832**	-8.508	1.214***	0.961***
	(0.058)	(0.508)	(0.347)	(42.610)	(0.274)	(0.049)
R-squared	0.500	0.376	0.545	NA	0.333	0.487
p-value $H_0: \beta_n = \beta_{n\alpha-k} = 0$	0.009	0.417	0.118	1.000	0.293	0.010
Observations	1,510	3,039	3,040	1,553	1,553	1,553

***p<0.01, **p<0.05, *p<0.1. Clustered robust standard errors in parentheses at the village level. Each column presents a separate regression, using inverse probability weights. Controls include time-invariant predictors (child's sex, birth order, child's language, ethnicity, region and area of residence at Round 1, religion, whether the child was severely or moderately underweight at Round 1, whether the child attended pre-primary education before aged 4, mother's age, main caregiver years of education; and time variant predictors (child's age in months, number of siblings living in household aged 0 to 12, a household wealth index, level of food and education expenditure per capita (in *Soles*), if family head is female) and village fixed effects. Reference categories: (Child's sex) Female, (Language) Other, (Birth order) First-born, (Underweight) Not underweighted (Ethnicity) Mestizo (includes Native of the Amazon, Negro & Asiatic), (Religion) Catholic, (Language) Other (Area) Urban, (Region) Coast.

Table B15. Alternative instruments: Time Inputs for Self-Efficacy index

CVA-IV	Instr: $PPVT_{t-1}$ (1)	Instr: $PPVT_{t-2}$ (2)	Instr: Self-$Esteem_{t-1}$ (3)	Instr: Self-$Esteem_{t-2}$ (4)	Instr: Self-$Esteem_{t-2}$ & $PPVT_{t-2}$ (5)	Instr: Self-$Efficacy_{t-2,}$ Self-$Esteem_{t-2}$ & $PPVT_{t-2}$ (6)
Education Time Inputs						
Hrs/day at school	0.024	0.021	0.032***	-0.039	0.021	0.020
	(0.035)	(0.031)	(0.010)	(1.037)	(0.032)	(0.033)
Hrs/day at $school_{t-1}$	-0.030	-0.008	0.047*	-0.469	-0.009	-0.011
	(0.077)	(0.069)	(0.027)	(6.789)	(0.070)	(0.069)
Hrs/day at $school_{t-2}$	-0.047	-0.038	-0.013	-0.227	-0.038	-0.039

CVA-IV	Instr: $PPVT_{t-1}$ (1)	Instr: $PPVT_{t-2}$ (2)	Instr: Self-$Esteem_{t-1}$ (3)	Instr: Self-$Esteem_{t-2}$ (4)	Instr: Self-$Esteem_{t-2}$ & $PPVT_{t-2}$ (5)	Instr: Self-$Efficacy_{t-2}$, Self-$Esteem_{t-2}$ & $PPVT_{t-2}$ (6)
	(0.063)	(0.063)	(0.028)	(2.884)	(0.063)	(0.065)
Hrs/day studying outside school	0.085	0.085	0.080***	0.089	0.085	0.085
	(0.063)	(0.053)	(0.023)	(0.389)	(0.054)	(0.056)
Hrs/day studying outside school$_{t-1}$	0.017	0.035	0.069***	-0.255	0.035	0.033
	(0.058)	(0.060)	(0.023)	(4.212)	(0.059)	(0.060)
Hrs/day studying outside school$_{t-2}$	-0.137**	-0.095	-0.037	-0.788	-0.096	-0.099
	(0.065)	(0.070)	(0.025)	(10.027)	(0.071)	(0.068)
<u>*Leisure Time Inputs*</u>						
Hrs/day in leisure activities	0.021	0.015	0.006	0.076	0.015	0.015
	(0.034)	(0.031)	(0.019)	(0.965)	(0.032)	(0.032)
Hrs/day in leisure activities$_{t-1}$	-0.001	0.015	0.010	-0.068	0.014	0.014
	(0.047)	(0.041)	(0.021)	(1.072)	(0.041)	(0.042)
Hrs/day in leisure activities$_{t-2}$	-0.064	-0.031	0.004	-0.464	-0.031	-0.033
	(0.045)	(0.041)	(0.020)	(6.173)	(0.041)	(0.039)
<u>*Child work Time Inputs*</u>						
Hrs/day in child work	-0.073**	-0.082***	-0.055***	-0.203	-0.083***	-0.084***
	(0.033)	(0.030)	(0.015)	(2.033)	(0.030)	(0.031)
Hrs/day in child work$_{t-1}$	0.008	0.007	0.001	0.060	0.007	0.008
	(0.036)	(0.034)	(0.018)	(0.813)	(0.034)	(0.035)
Hrs/day in child work$_{t-2}$	0.016	0.033	-0.001	0.122	0.033	0.034
	(0.045)	(0.049)	(0.019)	(1.660)	(0.049)	(0.051)
Self-Efficacy$_{t-1}$ (after instrument)	1.917***	1.655*	0.405***	11.073	1.672*	1.727*
	(0.409)	(0.922)	(0.132)	(141.585)	(0.913)	(0.904)
R-squared	NA	NA	0.15	NA	NA	NA
p-value $H_0: \beta_n = \beta_{n\alpha-k} = 0$	0.011	0.396	0.002	1.000	0.393	0.393
Observations	1,620	1555	1626	1626	1555	1555

***p<0.01, **p<0.05, *p<0.1. Clustered robust standard errors in parentheses at the village level. Each column presents a separate regression, using inverse probability weights. Controls include time-invariant predictors (child's sex, birth order, child's language, ethnicity, region and area of residence at Round 1, religion, whether the child was severely or moderately underweight at Round 1, whether the child attended pre-primary education before aged 4, mother's age, main caregiver years of education; and time variant predictors (child's age in months, number of siblings living in household aged 0 to 12, a household wealth index, level of food and education expenditure per capita (in *Soles*), if family head is female) and village fixed effects. Reference categories: (Child's sex) Female, (Language) Other, (Birth order) First-born, (Underweight) Not underweighted (Ethnicity) Mestizo (includes Native of the Amazon, Negro & Asiatic), (Religion) Catholic, (Language) Other (Area) Urban, (Region) Coast.

Table B16. Alternative instruments: Time Inputs for Self-Esteem index

CVA-IV	Instr: $PPVT_{t-1}$ (1)	Instr: $PPVT_{t-2}$ (2)	Instr: Self-$Efficacy_{t-1}$ (3)	Instr: Self-$Efficacy_{t-2}$ (4)	Instr: Self-$Esteem_{t-2}$ & $PPVT_{t-2}$ (5)	Instr: Self-$Efficacy_{t-2}$, Self-$Esteem_{t-2}$ & $PPVT_{t-2}$ (6)
<u>*Education Time Inputs*</u>						
Hrs/day at school	-0.016	0.023	0.007	0.003	0.008	0.012
	(0.132)	(0.042)	(0.015)	(0.027)	(0.022)	(0.018)
Hrs/day at school$_{t-1}$	-0.018	0.046	0.020	0.007	0.027	0.031
	(0.177)	(0.086)	(0.038)	(0.057)	(0.048)	(0.039)
Hrs/day at school$_{t-2}$	-0.233	0.069	-0.000	-0.051	-0.010	0.008
	(0.758)	(0.121)	(0.045)	(0.089)	(0.069)	(0.055)
Hrs/day studying outside school	-0.161	0.112	0.013	-0.026	0.004	0.029
	(0.581)	(0.162)	(0.025)	(0.070)	(0.057)	(0.035)
Hrs/day studying outside school$_{t-1}$	0.148	-0.013	0.033	0.061	0.060	0.043
	(0.378)	(0.078)	(0.027)	(0.057)	(0.038)	(0.028)
Hrs/day studying outside school$_{t-2}$	-0.339	0.050	-0.051	-0.117	-0.090	-0.058
	(0.952)	(0.225)	(0.034)	(0.112)	(0.080)	(0.052)

CVA-IV	*Instr: $PPVT_{t-1}$*	*Instr: $PPVT_{t-2}$*	*Instr: Self-Efficacy$_{t-1}$*	*Instr: Self-Efficacy$_{t-2}$*	*Instr: Self-Esteem$_{t-2}$ & $PPVT_{t-2}$*	*Instr: Self-Efficacy$_{t-2}$, Self-Esteem$_{t-2}$ & $PPVT_{t-2}$*
	(1)	(2)	(3)	(4)	(5)	(6)
Leisure Time Inputs						
Hrs/day in leisure activities	-0.011	-0.063*	-0.060***	-0.049*	-0.053***	-0.055***
	(0.187)	(0.036)	(0.018)	(0.026)	(0.017)	(0.017)
Hrs/day in leisure activities$_{t-1}$	0.276	-0.070	0.014	0.071	0.055	0.026
	(0.937)	(0.196)	(0.023)	(0.075)	(0.045)	(0.026)
Hrs/day in leisure activities$_{t-2}$	-0.026	-0.017	-0.013	-0.017	-0.020	-0.019
	(0.107)	(0.042)	(0.018)	(0.031)	(0.024)	(0.019)
Child work Time Inputs						
Hrs/day in child work	-0.083	0.011	-0.026**	-0.040	-0.044*	-0.031*
	(0.197)	(0.092)	(0.012)	(0.029)	(0.026)	(0.016)
Hrs/day in child work$_{t-1}$	-0.016	0.006	-0.002	-0.005	-0.002	0.000
	(0.097)	(0.038)	(0.016)	(0.032)	(0.024)	(0.017)
Hrs/day in child work$_{t-2}$	0.056	-0.080	-0.040**	-0.019	-0.034	-0.045**
	(0.363)	(0.084)	(0.016)	(0.044)	(0.030)	(0.019)
Self-Efficacy$_{t-1}$ (after instrument)	5.688	-1.645	0.317**	1.505	0.982	0.369
	(17.736)	(3.663)	(0.128)	(1.475)	(0.926)	(0.487)
R-squared	NA	NA	0.104	NA	NA	0.099
p-value $H_0: \beta_n = \beta_{n\alpha-k} = 0$	0.932	0.468	0.004	0.057	0.012	0.004
Observations	1,620	1,555	1,626	1,626	1,555	1,555

***p<0.01, **p<0.05, *p<0.1. Clustered robust standard errors in parentheses at the village level. Each column presents a separate regression, using inverse probability weights. Controls include time-invariant predictors (child's sex, birth order, child's language, ethnicity, region and area of residence at Round 1, religion, whether the child was severely or moderately underweight at Round 1, whether the child attended pre-primary education before aged 4, mother's age, main caregiver years of education; and time variant predictors (child's age in months, number of siblings living in household aged 0 to 12, a household wealth index, level of food and education expenditure per capita (in *Soles*), if family head is female) and village fixed effects. Reference categories: (Child's sex) Female, (Language) Other, (Birth order) First-born, (Underweight) Not underweighted (Ethnicity) Mestizo (includes Native of the Amazon, Negro & Asiatic), (Religion) Catholic, (Language) Other (Area) Urban, (Region) Coast.

Table B17. Sample distribution of children currently enrolled and at least one hr working

	Round 3 (Age 8)	*Round 4* (Age 12)	*Round 5* (Age 15)
Child currently enrolled (prop.)	0.759	0.921	0.891
Hrs/day in child work	2.067	2.806	2.657
	(1.341)	(1.688)	(1.721)
Observations	1273	1546	1495

*Sample of children from the paired analytic sample who reported currently being enrolled at least and working at least one hour daily.

Table B18. Child work trade-offs: PPVT score

	CVA				CVA-IV			
Omitted category:	*Leisure*	*Work*	*Study*	*School*	*Leisure*	*Work*	*Study*	*School*
	(1)	(2)	(3)	(4)	(5)	(6)	(5	(6)
Education Time Inputs								
Hrs/day at school	0.015**	0.015**	0.009		0.004	0.001	-0.002	
	(0.005)	(0.006)	(0.006)		(0.006)	(0.009)	(0.007)	
Hrs/day at school$_{t-1}$	0.007	0.013	0.005		-0.006	-0.002	-0.008	
	(0.011)	(0.010)	(0.011)		(0.010)	(0.011)	(0.011)	
Hrs/day at school$_{t-2}$	0.006	0.011*	0.012*		0.003	0.006	0.006	
	(0.005)	(0.006)	(0.006)		(0.009)	(0.009)	(0.009)	

	CVA				CVA-IV			
Omitted category:	*Leisure*	*Work*	*Study*	*School*	*Leisure*	*Work*	*Study*	*School*
	(1)	(2)	(3)	(4)	(5)	(6)	(5	(6)
Hrs/day studying outside school	0.019**	0.018**		0.012	0.010	0.007		0.006
	(0.007)	(0.008)		(0.008)	(0.009)	(0.009)		(0.009)
Hrs/day studying outside school$_{t-1}$	0.026***	0.030***		0.027***	0.013	0.015		0.013
	(0.007)	(0.008)		(0.008)	(0.010)	(0.010)		(0.010)
Hrs/day studying outside school$_{t-2}$	0.011	0.017*		0.018*	-0.012	-0.008		-0.006
	(0.009)	(0.010)		(0.010)	(0.010)	(0.010)		(0.011)
Leisure Time Inputs								
Hrs/day in leisure activities		-0.005	-0.010*	-0.011*		-0.010*	-0.011**	-0.010*
		(0.005)	(0.005)	(0.006)		(0.006)	(0.005)	(0.005)
Hrs/day in leisure activities$_{t-1}$		0.009	-0.002	0.002		0.004	-0.004	-0.001
		(0.006)	(0.005)	(0.005)		(0.006)	(0.006)	(0.005)
Hrs/day in leisure activities$_{t-2}$		0.011**	0.005	0.005		0.007	0.009	0.007
		(0.005)	(0.005)	(0.005)		(0.006)	(0.007)	(0.007)
R-squared	0.593	0.591	0.591	0.592	0.467	0.470	0.470	0.468
p-value $H_0: \beta_n = \beta_{n\alpha-k} = 0$	0.002	0.201	0.018	0.004	0.052	0.235	0.000	0.000
Observations	2759	2759	2759	2759	2759	2759	2759	2759

***p<0.01, **p<0.05, *p<0.1. Clustered robust standard errors in parentheses at the village level. Each column presents a separate regression, using inverse probability weights.

Table B19. Child work trade-offs: Self-Esteem

	CVA			
Omitted category:	*Leisure*	*Work*	*Study*	*School*
	(1)	(2)	(3)	(4)
Education Time Inputs				
Hrs/day at school	0.031**	0.014	0.004	
	(0.012)	(0.015)	(0.018)	
Hrs/day at school$_{t-1}$	0.022	0.022	0.017	
	(0.031)	(0.028)	(0.029)	
Hrs/day at school$_{t-2}$	0.009	0.016	0.016	
	(0.016)	(0.016)	(0.015)	
Hrs/day studying outside school	0.039*	0.024		0.013
	(0.021)	(0.024)		(0.022)
Hrs/day studying outside school$_{t-1}$	0.029	0.033		0.029
	(0.022)	(0.022)		(0.023)
Hrs/day studying outside school$_{t-2}$	0.025	0.029		0.033
	(0.035)	(0.035)		(0.033)
Leisure Time Inputs				
Hrs/day in leisure activities		-0.044***	-0.059***	-0.058***
		(0.015)	(0.019)	(0.015)
Hrs/day in leisure activities$_{t-1}$		0.009	-0.003	0.000
		(0.013)	(0.016)	(0.017)
Hrs/day in leisure activities$_{t-2}$		0.014*	0.004	0.005
		(0.008)	(0.009)	(0.010)
R-squared	0.077	0.077	0.080	0.081
p-value $H_0: \beta_n = \beta_{n\alpha-k} = 0$	0.241	0.108	0.025	0.004
Observations	2,757	2,757	2,757	2,757

***p<0.01, **p<0.05, *p<0.1. Clustered robust standard errors in parentheses at the village level. Each column presents a separate regression, using inverse probability weights.

Table B20. FE Coefficients on Time Inputs (all controls)

	PPVT (1)	*Self-Efficacy* (2)	*Self-Esteem* (3)
Head of household is female	-0.036 (0.030)	0.049 (0.095)	-0.004 (0.099)
Child's age (in months)	-0.004 (0.007)	-0.024 (0.021)	-0.025 (0.023)
Number of males aged 0-5	-0.001 (0.022)	0.108* (0.059)	-0.018 (0.068)
Number of females aged 0-5	-0.033 (0.022)	0.137** (0.063)	0.024 (0.060)
Number of males aged 6-12	0.000 (0.024)	-0.031 (0.067)	0.074 (0.067)
Number of females aged 6-12	-0.021 (0.025)	0.073 (0.072)	-0.040 (0.066)
Wealth index	0.108 (0.074)	-0.318 (0.245)	0.100 (0.240)
Monthly expenditure in education items per capita	-0.000 (0.001)	0.001 (0.001)	-0.001 (0.001)
Monthly expenditure in food items per capita	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Constant	1.396 (1.331)	4.643 (3.886)	4.349 (4.131)
R-squared	0.538	0.249	0.216
p-value $H_0: \beta_n = \beta_{n\alpha-k} = 0$	0.279	0.007	0.073
Observations (children-data points)	3,146	3,146	3,146
Number of children	1,662	1,662	1,662

***p<0.01, **p<0.05, *p<0.1. Clustered robust standard errors in parentheses at the village level. Each column presents a separate regression. Controls include time variant predictors (child's age in months, number of siblings living in household aged 0 to 12, a household wealth index, level of food and education expenditure per capita (in *Soles*), an indicator if family head is female), village and child fixed effects.

Table C1. Mean and variation of outcomes and controls

	Mean	*SD*	$SD_{between}$	SD_{within}
Outcomes				
School enrolment	0.716	0.451	0.348	0.297
Child work participation	0.615	0.487	0.394	0.305
Hrs/day at school	5.984	1.138	1.012	0.659
Hrs/day studying outside school	2.008	0.910	0.757	0.544
Hrs/day in leisure activities	4.158	1.708	1.481	1.002
Hrs/day in child-working activities	1.682	1.660	1.364	0.966
Child Characteristics				
Age (in years)	9.228	2.843	2.302	1.896
Birth order	1.449	0.498	0.500	0.000
Female (prop.)	0.504	0.500	0.500	0.000
Children attended preschool (prop.)	0.965	0.184	0.192	0.000
Language is Spanish (prop.)	0.954	0.209	0.219	0.000
Religion is Catholic (prop.)	0.839	0.368	0.370	0.000
Other religion (prop.)	0.107	0.309	0.312	0.000
Ethnicity is Mestizo (prop.)	0.894	0.307	0.307	0.000
Ethnicity is White (prop.)	0.081	0.273	0.272	0.000

	Mean	*SD*	*SD*$_{between}$	*SD*$_{within}$
Household Characteristics				
Number of siblings	2.000	0.000	0.000	0.000
Wealth index	0.647	0.181	0.170	0.065
Household owned any livestock in the past 12 months	0.492	0.500	0.447	0.235
Monthly expenditure in food items per capita	154.105	79.594	67.654	45.041
Parental Characteristics				
Mom age (at birth)	24.463	5.471	5.399	0.000
Caregiver years of education (at birth)	9.912	3.865	3.898	0.000
Head of household is female (prop.)	0.167	0.373	0.339	0.165
Region Characteristics				
Child lives in Coast region (prop.)	0.451	0.498	0.498	0.000
Child lives in Mountain region (prop.)	0.412	0.492	0.493	0.000
Child lives in Jungle region (prop.)	0.138	0.345	0.343	0.000
Child lives in Urban area (prop.)	0.821	0.383	0.384	0.000
Child lives in Rural area (prop.)	0.179	0.383	0.384	0.000
Observations (Children)	734			
Observations (Children-Data points)	1336			

*Descriptive statistics for analytic sample (n = 1336)

Table C2. CRE estimates: binary indicators (all coefficients)

	School enrolment (I)	*Child work* (II)
Birth order (*j* =2)	-0.106	-0.435***
	(0.124)	(0.134)
Age in years (age=5)	0.887*	0.401
	(0.481)	(0.285)
Age in years (age=6)	-1.061***	0.664**
	(0.315)	(0.309)
Age in years (age=7)	-0.491*	1.197***
	(0.257)	(0.240)
Age in years (age=8)	-0.488*	1.093***
	(0.256)	(0.237)
Age in years (age=9)	0.107	1.548***
	(0.388)	(0.358)
Age in years (age=10)	-0.421	0.805**
	(0.359)	(0.345)
Age in years (age=11)	-0.154	2.298***
	(0.288)	(0.307)
Age in years (age=12)	-1.724***	-0.280
	(0.287)	(0.274)
Age in years (age=13)	-1.683***	0.250
	(0.399)	(0.388)
Age in years (age=14)	-1.397***	0.165
	(0.410)	(0.411)
Age in years (age=15)	-1.992***	
	(0.504)	
Age in years (age=16)	-2.194***	-1.252*
	(0.489)	(0.653)

	School enrolment	*Child work*
	(I)	(II)
Age in years (age=17)	-1.691***	-1.183**
	(0.466)	(0.560)
Child is female	0.077	0.146
	(0.088)	(0.093)
Wealth index	-0.480	-0.475
	(0.575)	(0.608)
Household owned any livestock in the past 12 months	-0.008	0.024
	(0.150)	(0.156)
Monthly expenditure in food items per capita	-0.000	-0.000
	(0.001)	(0.001)
Mom age at Round 1 (YL child age~)	0.002	0.013
	(0.011)	(0.011)
Caregiver years of education at Round 1	-0.001	-0.049***
	(0.016)	(0.017)
Head of household is female	0.036	-0.441**
	(0.214)	(0.223)
Children attended preschool	0.481**	0.310
	(0.216)	(0.246)
Child speaks Spanish	0.180	-0.516
	(0.262)	(0.333)
Child religion Catholic	-0.566**	0.042
	(0.234)	(0.206)
Child religion is Other	-0.578**	0.200
	(0.260)	(0.248)
Child ethnicity is White	-0.470	-0.092
	(0.388)	(0.376)
Child ethnicity is Mestizo	-0.378	0.254
	(0.352)	(0.345)
Child lived at Coast	0.256	0.989**
	(0.367)	(0.418)
Child lived at Mountain	-0.205	0.506
	(0.338)	(0.396)
Child lived Urban area	-0.105	-0.205
	(0.188)	(0.209)
Year gap between siblings (year gap=2)	-0.653**	-0.634**
	(0.286)	(0.284)
Year gap between siblings (year gap=3)	-0.518*	-0.342
	(0.288)	(0.291)
Year gap between siblings (year gap=4)	-0.282	-0.508*
	(0.301)	(0.301)
Year gap between siblings (year gap=5)	-0.627**	-0.367
	(0.284)	(0.290)
Year gap between siblings (year gap=6)	-0.608**	-0.506*
	(0.288)	(0.292)
Year gap between siblings (year gap=7)	-0.532*	-0.617**
	(0.306)	(0.302)
Year gap between siblings (year gap=8)	-0.852***	-0.946***
	(0.318)	(0.324)
Year gap between siblings (year gap=9)	-0.732**	-0.466
	(0.325)	(0.332)
Year gap between siblings (year gap=10)	-0.751**	-0.808**
	(0.354)	(0.368)
Year gap between siblings (year gap=11)	-0.054	-0.223
	(0.362)	(0.371)
Year gap between siblings (year gap=12)	-0.315	0.505
	(0.569)	(0.600)
Year gap between siblings (year gap=13)		-0.215
		(0.770)

	School enrolment (I)	*Child work* (II)
Year gap between siblings (year gap=14)	-0.771	-0.408
	(1.144)	(1.162)
Year gap between siblings (year gap=15)		
Year gap between siblings (year gap=26)		-2.214*
		(1.152)
Family cluster-mean: Head of household is female	-0.229	0.358
	(0.281)	(0.301)
Family cluster-mean: wealth index	1.028	0.112
	(0.663)	(0.722)
Family cluster-mean: HH owned livestock past 12 months	-0.081	0.137
	(0.199)	(0.210)
Family cluster-mean: Food expenditure per capita	0.001	-0.001
	(0.001)	(0.001)
Observations (children-data points)	1,324	1,320
Observations (children)	728	733
Observations (families)	458	458
p-value $H_0: \beta_1 = \beta_2 = 0$	0.393	0.001
p-value $H_0: \pi = 0$	0.296	0.630

***p<0.001, **p<0.01, *p<0.05. Clustered robust standard errors at the family level in parentheses. Each column presents a separate regression.

Table C3. CRE Average Marginal Effects for binary indicators

	School enrolment (I)	*Child work* (II)
Birth order (=2)	-0.026	-0.107***
	(0.031)	(0.033)
Age in years (age=5)	0.085*	0.127
	(0.043)	(0.089)
Age in years (age=6)	-0.283***	0.213*
	(0.084)	(0.097)
Age in years (age=7)	-0.105*	0.376***
	(0.048)	(0.069)
Age in years (age=8)	-0.104*	0.346***
	(0.047)	(0.069)
Age in years (age=9)	0.017	0.464***
	(0.059)	(0.090)
Age in years (age=10)	-0.087	0.258*
	(0.077)	(0.107)
Age in years (age=11)	-0.028	0.585***
	(0.050)	(0.071)
Age in years (age=12)	-0.522***	-0.080
	(0.065)	(0.080)
Age in years (age=13)	-0.507***	0.078
	(0.116)	(0.122)
Age in years (age=14)	-0.404**	0.051
	(0.123)	(0.128)
Age in years (age=15)	-0.611***	
	(0.142)	
Age in years (age=16)	-0.670***	-0.268**
	(0.124)	(0.101)
Age in years (age=17)	-0.510***	-0.259**
	(0.141)	(0.097)
Child is female	0.019	0.036
	(0.022)	(0.023)

	School enrolment (I)	*Child work* (II)
Mom age at Round 1 (YL child age~)	0.001 (0.003)	0.003 (0.003)
Caregiver years of education at Round 1	0.000 (0.004)	-0.012** (0.004)
Head of household is female	0.009 (0.053)	-0.108* (0.054)
Wealth index	-0.12 (0.143)	-0.116 (0.149)
Household owned any livestock in the past 12 months	-0.002 (0.037)	0.006 (0.038)
Monthly expenditure in food items per capita	0.000 (0.000)	0.000 (0.000)
Children attended preschool	0.120* (0.054)	0.076 (0.06)
Year gap between siblings (year gap=2)	-0.146* (0.057)	-0.150* (0.063)
Year gap between siblings (year gap=3)	-0.111* (0.056)	-0.078 (0.064)
Year gap between siblings (year gap=4)	-0.057 (0.058)	-0.118 (0.067)
Year gap between siblings (year gap=5)	-0.139* (0.056)	-0.084 (0.064)
Year gap between siblings (year gap=6)	-0.134* (0.058)	-0.118 (0.065)
Year gap between siblings (year gap=7)	-0.115 (0.061)	-0.145* (0.068)
Year gap between siblings (year gap=8)	-0.200** (0.069)	-0.229** (0.073)
Year gap between siblings (year gap=9)	-0.167* (0.070)	-0.108 (0.075)
Year gap between siblings (year gap=10)	-0.172* (0.080)	-0.194* (0.086)
Year gap between siblings (year gap=11)	-0.010 (0.067)	-0.050 (0.083)
Year gap between siblings (year gap=12)	-0.064 (0.122)	0.097 (0.106)
Year gap between siblings (year gap=13)		-0.048 (0.176)
Year gap between siblings (year gap=14)	-0.178 (0.309)	-0.093 (0.280)
Year gap between siblings (year gap=26)		-0.526* (0.217)
Child speaks Spanish	0.045 (0.065)	-0.126 (0.081)
Child religion Catholic	-0.141* (0.058)	0.010 (0.050)
Child religion is Other	-0.144* (0.065)	0.049 (0.061)
Child ethnicity is White	-0.117 (0.097)	-0.022 (0.092)
Child ethnicity is Mestizo	-0.094 (0.088)	0.062 (0.084)
Child lived at Coast	0.064 (0.091)	0.242* (0.102)
Child lived at Mountain	-0.051 (0.084)	0.124 (0.097)
Child lived Urban area	-0.026 (0.047)	-0.050 (0.051)

***p<0.001, **p<0.01, *p<0.05. Clustered robust standard errors at the family level in parentheses. Each column presents a separate regression.

Table C4. Average Marginal Effects: bivariate probit

	Joint: School enrolment & Child work (I)	*School enrolment* (II)	*Child work participation* (III)
AME: Birth order (j =2)	-0.091*	-0.026*	-0.004
	(0.036)	(0.010)	(0.008)
p-value $H_0: \beta_1 = \beta_2 = 0$	0.011		
Observations	1336		

***p<0.001, **p<0.01, *p<0.05. Standard errors in parentheses. Each column presents average marginal effects from a joint bivariate probit equation.

Table C5. CRE estimates

	Hrs/day at school (I)	*Hrs/day studying outside school* (II)	*Hrs/day in leisure* (III)	*Hrs/day in child-work* (IV)
Birth order (j =2)	-0.120*	0.071	0.328***	-0.813***
	(0.071)	(0.062)	(0.118)	(0.104)
Age in years (age=5)	0.968***	0.217*	-0.707**	0.127
	(0.222)	(0.128)	(0.284)	(0.171)
Age in years (age=6)	1.211***	0.711***	-1.258***	0.246
	(0.253)	(0.174)	(0.308)	(0.196)
Age in years (age=7)	1.541***	0.688***	-1.556***	0.423***
	(0.185)	(0.107)	(0.230)	(0.159)
Age in years (age=8)	1.593***	0.755***	-1.787***	0.450***
	(0.184)	(0.107)	(0.238)	(0.141)
Age in years (age=9)	1.833***	1.112***	-2.209***	1.143***
	(0.214)	(0.194)	(0.279)	(0.259)
Age in years (age=10)	1.578***	1.128***	-1.538***	0.204
	(0.264)	(0.157)	(0.440)	(0.269)
Age in years (age=11)	1.663***	0.940***	-2.490***	1.581***
	(0.181)	(0.125)	(0.251)	(0.184)
Age in years (age=12)	1.850***	1.175***	-2.514***	0.984***
	(0.191)	(0.129)	(0.258)	(0.185)
Age in years (age=13)	2.214***	1.240***	-2.905***	1.453***
	(0.273)	(0.194)	(0.416)	(0.365)
Age in years (age=14)	1.827***	1.134***	-2.321***	1.433***
	(0.298)	(0.237)	(0.485)	(0.373)
Age in years (age=15)	1.720***	1.699***	-2.583***	1.095*
	(0.363)	(0.391)	(0.570)	(0.570)
Age in years (age=16)	1.340***	1.271***	-2.828***	2.166***
	(0.436)	(0.306)	(0.481)	(0.645)
Age in years (age=17)	0.698	1.427***	-2.184***	2.863***
	(0.686)	(0.493)	(0.566)	(0.816)
Child is female	0.075	0.140***	-0.276***	0.141*
	(0.062)	(0.049)	(0.090)	(0.075)
Wealth index	-0.707*	-0.565*	1.235*	-0.708
	(0.407)	(0.294)	(0.723)	(0.574)
Household owned any livestock in the past 12 months	0.032	-0.055	-0.156	0.116
	(0.091)	(0.091)	(0.163)	(0.134)
Monthly expenditure in food items per capita	-0.001	-0.001**	0.003***	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Mom age at Round 1 (YL child age~)	-0.001	-0.010*	-0.005	0.015
	(0.007)	(0.006)	(0.012)	(0.011)
Caregiver years of education at Round 1	0.008	0.036***	0.019	-0.045***
	(0.012)	(0.008)	(0.020)	(0.016)
Head of household is female	0.005	-0.089	-0.021	-0.037
	(0.126)	(0.112)	(0.225)	(0.210)

	Hrs/day at school	*Hrs/day studying outside school*	*Hrs/day in leisure*	*Hrs/day in child-work*
	(I)	(II)	(III)	(IV)
Children attended preschool	1.399***	0.278	-0.768	-0.132
	(0.399)	(0.198)	(0.467)	(0.419)
Child speaks Spanish	0.060	-0.079	-0.052	-0.160
	(0.275)	(0.167)	(0.302)	(0.272)
Child religion Catholic	-0.312***	-0.180	-0.060	0.109
	(0.116)	(0.135)	(0.209)	(0.152)
Child religion is Other	-0.284*	-0.314**	-0.061	0.368*
	(0.148)	(0.146)	(0.261)	(0.205)
Child ethnicity is White	-0.340	-0.114	0.814**	-0.045
	(0.275)	(0.152)	(0.402)	(0.366)
Child ethnicity is Mestizo	-0.311	-0.166	0.565	0.241
	(0.251)	(0.126)	(0.362)	(0.342)
Child lived at Coast	0.295	0.112	-0.782*	0.589**
	(0.274)	(0.194)	(0.417)	(0.263)
Child lived at Mountain	0.065	0.278	-0.020	0.276
	(0.220)	(0.191)	(0.404)	(0.263)
Child lived Urban area	-0.127	0.025	0.128	0.266
	(0.127)	(0.110)	(0.178)	(0.165)
Year gap between siblings (year gap=2)	-0.254	0.048	0.259	-0.546**
	(0.203)	(0.149)	(0.320)	(0.239)
Year gap between siblings (year gap=3)	-0.129	-0.024	0.109	-0.264
	(0.203)	(0.153)	(0.298)	(0.235)
Year gap between siblings (year gap=4)	0.054	-0.006	-0.182	-0.044
	(0.203)	(0.155)	(0.303)	(0.267)
Year gap between siblings (year gap=5)	-0.219	0.066	0.129	-0.364
	(0.213)	(0.159)	(0.305)	(0.242)
Year gap between siblings (year gap=6)	-0.147	0.009	0.079	-0.189
	(0.211)	(0.159)	(0.299)	(0.240)
Year gap between siblings (year gap=7)	-0.192	-0.050	0.338	-0.451*
	(0.204)	(0.154)	(0.299)	(0.236)
Year gap between siblings (year gap=8)	-0.258	0.067	0.461	-0.730***
	(0.205)	(0.167)	(0.338)	(0.244)
Year gap between siblings (year gap=9)	-0.284	-0.080	0.402	-0.556**
	(0.243)	(0.178)	(0.382)	(0.277)
Year gap between siblings (year gap=10)	-0.224	0.282*	0.185	-0.922***
	(0.246)	(0.170)	(0.381)	(0.255)
Year gap between siblings (year gap=11)	0.131	0.229	-0.053	-0.658**
	(0.256)	(0.208)	(0.364)	(0.269)
Year gap between siblings (year gap=12)	-0.050	0.014	-0.531	0.166
	(0.331)	(0.323)	(0.578)	(0.304)
Year gap between siblings (year gap=13)	0.756*	0.362	0.023	-0.146
	(0.424)	(0.270)	(0.512)	(0.382)
Year gap between siblings (year gap=14)	-0.500**	0.183	0.071	0.503
	(0.249)	(0.188)	(0.379)	(0.310)
Year gap between siblings (year gap=15)	-0.320	-0.025	-0.991**	1.258***
	(0.271)	(0.203)	(0.399)	(0.288)
Year gap between siblings (year gap=26)	-1.569***	1.083***	1.167***	-1.195***
	(0.279)	(0.206)	(0.391)	(0.329)
Family cluster-mean: Head of household is female	-0.324*	-0.042	0.167	0.254
	(0.175)	(0.177)	(0.284)	(0.263)
Family cluster-mean: wealth index	1.536***	0.600	-1.344*	-0.365
	(0.458)	(0.382)	(0.748)	(0.621)
Family cluster-mean: HH owned livestock past 12 months	-0.155	-0.034	0.149	0.115
	(0.134)	(0.127)	(0.214)	(0.173)

	Hrs/day at school (I)	*Hrs/day studying outside school* (II)	*Hrs/day in leisure* (III)	*Hrs/day in child-work* (IV)
Family cluster-mean: Food expenditure per capita	0.001	0.002*	-0.004**	0.000
	(0.001)	(0.001)	(0.002)	(0.001)
Observations (children-data points)	1,336	1,336	1,336	1,336
Observations (children)	734	734	734	734
Observations (families)	458	458	458	458
p-value $H_0: \beta_1 = \beta_2 = 0$	0.092	0.251	0.005	0.000
p-value $H_0: \pi = 0$	0.000	0.085	0.022	0.785
R-squared	0.293	0.207	0.260	0.360

***p<0.001, **p<0.01, *p<0.05. Clustered robust standard errors at the family level in parentheses. Each column presents a separate regression.

Table C6. CRE estimates: child work disaggregated (all coefficients)

	Hrs/day care (V)	*Hrs/day chores* (VI)	*Hrs/day tasks* (VII)	*Hrs/day paid work* (VIII)
Birth order (*j* =2)	-0.808***	0.024	0.003	-0.001
	(0.054)	(0.048)	(0.055)	(0.024)
Age in years (age=5)	-0.021	0.178*	0.011	-0.031
	(0.062)	(0.103)	(0.071)	(0.060)
Age in years (age=6)	-0.050	0.377***	-0.026	-0.046
	(0.071)	(0.126)	(0.085)	(0.070)
Age in years (age=7)	-0.151**	0.472***	0.158**	-0.067
	(0.059)	(0.081)	(0.070)	(0.068)
Age in years (age=8)	-0.073	0.441***	0.158**	-0.061
	(0.053)	(0.082)	(0.069)	(0.070)
Age in years (age=9)	0.182	0.786***	0.154	-0.016
	(0.112)	(0.145)	(0.103)	(0.065)
Age in years (age=10)	-0.285**	0.501***	0.046	-0.053
	(0.127)	(0.133)	(0.096)	(0.069)
Age in years (age=11)	0.374***	0.882***	0.302***	-0.025
	(0.084)	(0.093)	(0.104)	(0.074)
Age in years (age=12)	0.047	0.771***	0.141*	0.011
	(0.085)	(0.097)	(0.084)	(0.091)
Age in years (age=13)	-0.133	0.996***	0.480**	0.123
	(0.209)	(0.155)	(0.200)	(0.143)
Age in years (age=14)	0.173	1.081***	0.116	0.010
	(0.238)	(0.180)	(0.131)	(0.101)
Age in years (age=15)	-0.256	1.216***	-0.024	-0.066
	(0.216)	(0.344)	(0.197)	(0.355)
Age in years (age=16)	-0.086	1.203***	0.314	0.248
	(0.259)	(0.233)	(0.218)	(0.274)
Age in years (age=17)	-0.143	1.025***	0.938*	0.596
	(0.264)	(0.265)	(0.512)	(0.435)
Child is female	0.038	0.094**	-0.003	-0.021
	(0.041)	(0.038)	(0.034)	(0.017)
Wealth index	-0.231	-0.205	-0.365	0.124
	(0.277)	(0.283)	(0.310)	(0.114)
Household owned any livestock in the past 12 months	0.046	0.019	0.107	-0.036
	(0.068)	(0.078)	(0.067)	(0.028)
Monthly expenditure in food items per capita	-0.001	0.001	0.000	-0.000
	(0.000)	(0.001)	(0.001)	(0.000)

	Hrs/day care	*Hrs/day chores*	*Hrs/day tasks*	*Hrs/day paid work*
	(V)	(VI)	(VII)	(VIII)
Mom age at Round 1 (YL child age~)	0.004	0.007	0.005	-0.002
	(0.004)	(0.005)	(0.005)	(0.003)
Caregiver years of education at Round 1	-0.008	-0.010	-0.018**	-0.003
	(0.008)	(0.007)	(0.008)	(0.003)
Head of household is female	-0.009	-0.015	-0.097	0.021
	(0.097)	(0.099)	(0.110)	(0.049)
Children attended preschool	-0.049	0.007	-0.211	0.079*
	(0.100)	(0.145)	(0.282)	(0.047)
Child speaks Spanish	-0.054	0.017	-0.076	-0.142
	(0.109)	(0.135)	(0.176)	(0.133)
Child religion Catholic	-0.023	0.123	0.030	-0.032
	(0.086)	(0.101)	(0.079)	(0.041)
Child religion is Other	0.096	0.314***	-0.038	-0.052
	(0.107)	(0.121)	(0.092)	(0.049)
Child ethnicity is White	0.009	0.097	-0.045	-0.056
	(0.136)	(0.228)	(0.143)	(0.065)
Child ethnicity is Mestizo	0.080	0.239	-0.045	-0.031
	(0.118)	(0.212)	(0.143)	(0.068)
Child lived at Coast	0.223	0.168	0.081	0.070
	(0.137)	(0.157)	(0.126)	(0.056)
Child lived at Mountain	0.107	-0.125	0.242	0.010
	(0.124)	(0.117)	(0.203)	(0.061)
Child lived Urban area	0.122	-0.108	0.153	0.077*
	(0.085)	(0.074)	(0.108)	(0.039)
Year gap between siblings (year gap=2)	-0.038	-0.128	-0.269	-0.028
	(0.094)	(0.116)	(0.168)	(0.029)
Year gap between siblings (year gap=3)	0.023	-0.022	-0.190	0.020
	(0.101)	(0.113)	(0.167)	(0.038)
Year gap between siblings (year gap=4)	0.129	-0.005	-0.207	0.083
	(0.115)	(0.118)	(0.177)	(0.069)
Year gap between siblings (year gap=5)	0.091	-0.067	-0.218	-0.072*
	(0.103)	(0.111)	(0.181)	(0.043)
Year gap between siblings (year gap=6)	0.139	-0.136	-0.094	-0.018
	(0.105)	(0.112)	(0.181)	(0.029)
Year gap between siblings (year gap=7)	0.003	-0.065	-0.264	-0.042
	(0.112)	(0.118)	(0.164)	(0.029)
Year gap between siblings (year gap=8)	-0.134	-0.142	-0.296*	-0.040
	(0.122)	(0.124)	(0.166)	(0.031)
Year gap between siblings (year gap=9)	-0.199	-0.029	-0.243	0.049
	(0.132)	(0.120)	(0.170)	(0.077)
Year gap between siblings (year gap=10)	-0.305***	-0.112	-0.415**	-0.004
	(0.111)	(0.132)	(0.167)	(0.037)
Year gap between siblings (year gap=11)	-0.171	-0.129	-0.195	-0.021
	(0.123)	(0.135)	(0.181)	(0.028)
Year gap between siblings (year gap=12)	-0.198	0.092	0.391	0.005
	(0.222)	(0.255)	(0.376)	(0.038)
Year gap between siblings (year gap=13)	-0.187	0.202	-0.121	-0.025
	(0.140)	(0.208)	(0.342)	(0.061)
Year gap between siblings (year gap=14)	-0.002	0.449***	-0.413**	0.096*
	(0.128)	(0.152)	(0.196)	(0.055)
Year gap between siblings (year gap=15)	-0.224*	0.287*	1.307***	0.042
	(0.132)	(0.153)	(0.170)	(0.052)
Year gap between siblings (year gap=26)	0.228	-0.831***	-0.511***	0.062

	Hrs/day care (V)	Hrs/day chores (VI)	Hrs/day tasks (VII)	Hrs/day paid work (VIII)
	(0.141)	(0.174)	(0.184)	(0.064)
Family cluster-mean: Head of household is female	0.084	0.025	0.149	0.038
	(0.128)	(0.127)	(0.147)	(0.082)
Family cluster-mean: wealth index	-0.001	-0.255	0.078	-0.205
	(0.312)	(0.320)	(0.349)	(0.147)
Family cluster-mean: HH owned livestock past 12 months	-0.060	-0.017	0.079	0.065*
	(0.086)	(0.098)	(0.091)	(0.035)
Family cluster-mean: Food expenditure per capita	0.000	-0.001	-0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Observations (children-data points)	1,336	1,336	1,336	1,336
Observations (children)	734	734	734	734
Observations (families)	458	458	458	458
p-value $H_0: \beta_1 = \beta_2 = 0$	0.000	0.608	0.957	0.963
p-value $H_0: \pi = 0$	0.800	0.579	0.744	0.390
R-squared	0.313	0.233	0.172	0.080

***p<0.001, **p<0.01, *p<0.05. Clustered robust standard errors at the family level in parentheses. Each column presents a separate regression.

Table C7. Sensitivity CRE: Family Size (all coefficients)

	2 siblings				**3 siblings**			
	Hrs/day at school (Ia)	*Hrs/day studying outside school* (IIa)	*Hrs/day in leisure* (IIIa)	*Hrs/day in child-work* (IVa)	*Hrs/day at school* (Ib)	*Hrs/day studying outside school* (IIb)	*Hrs/day in leisure* (IIIb)	*Hrs/day in child-work* (IVb)
Birth order (*j* =2)	-0.136	0.082	0.280*	-0.682***	-0.092	-0.017	0.276**	-0.150
	(0.091)	(0.076)	(0.151)	(0.128)	(0.086)	(0.065)	(0.115)	(0.136)
Birth order (*j* =3)					-0.151	-0.084	0.534***	-0.681***
					(0.139)	(0.099)	(0.189)	(0.173)
Age in years (age=5)	0.964***	0.220	-0.597*	0.098	0.685**	0.308*	-0.961***	-0.065
	(0.241)	(0.155)	(0.339)	(0.214)	(0.272)	(0.160)	(0.356)	(0.157)
Age in years (age=6)	1.168***	0.673***	-1.113***	0.280	1.129***	0.431***	-1.373***	0.365**
	(0.274)	(0.200)	(0.319)	(0.230)	(0.253)	(0.148)	(0.362)	(0.186)
Age in years (age=7)	1.459***	0.665***	-1.573***	0.391**	1.569***	0.700***	-1.680***	0.682***
	(0.205)	(0.126)	(0.256)	(0.195)	(0.225)	(0.132)	(0.323)	(0.153)
Age in years (age=8)	1.511***	0.734***	-1.764***	0.486***	1.463***	0.641***	-1.787***	0.811***
	(0.205)	(0.127)	(0.258)	(0.178)	(0.217)	(0.136)	(0.300)	(0.160)
Age in years (age=9)	1.727***	1.064***	-2.042***	1.559***	1.647***	0.857***	-2.299***	1.290***
	(0.267)	(0.215)	(0.355)	(0.369)	(0.252)	(0.161)	(0.361)	(0.227)
Age in years (age=10)	1.592***	1.086***	-1.926***	0.178	1.393***	0.790***	-2.350***	1.471***
	(0.306)	(0.185)	(0.423)	(0.350)	(0.228)	(0.162)	(0.356)	(0.285)
Age in years (age=11)	1.612***	0.860***	-2.423***	1.754***	1.601***	0.761***	-2.422***	1.744***
	(0.200)	(0.138)	(0.286)	(0.215)	(0.232)	(0.146)	(0.334)	(0.194)
Age in years (age=12)	1.747***	1.139***	-2.440***	1.144***	1.807***	0.878***	-2.627***	1.692***
	(0.215)	(0.141)	(0.301)	(0.217)	(0.223)	(0.156)	(0.325)	(0.199)
Age in years (age=13)	2.075***	1.223***	-2.800***	1.380***	2.158***	0.810***	-2.884***	2.066***
	(0.315)	(0.208)	(0.492)	(0.418)	(0.327)	(0.209)	(0.453)	(0.323)
Age in years (age=14)	1.786***	1.136***	-2.816***	1.796***	1.716***	0.791***	-3.131***	2.461***
	(0.327)	(0.297)	(0.594)	(0.455)	(0.297)	(0.208)	(0.474)	(0.390)
Age in years (age=15)	1.599***	1.358***	-3.170***	2.111***	1.506***	0.537**	-2.555***	3.425***
	(0.445)	(0.442)	(0.502)	(0.722)	(0.373)	(0.218)	(0.461)	(0.666)
Age in years (age=16)	1.182**	1.102***	-2.545***	2.502***	1.328***	0.692**	-2.969***	3.047***
	(0.483)	(0.340)	(0.531)	(0.721)	(0.454)	(0.275)	(0.427)	(0.614)

	2 siblings				3 siblings			
	Hrs/day at school	*Hrs/day studying outside school*	*Hrs/day in leisure*	*Hrs/day in child-work*	*Hrs/day at school*	*Hrs/day studying outside school*	*Hrs/day in leisure*	*Hrs/day in child-work*
	(Ia)	(IIa)	(IIIa)	(IVa)	(Ib)	(IIb)	(IIIb)	(IVb)
Age in years (age=17)	0.618	1.355***	-2.100***	3.067***	-0.340	0.665	-2.741***	3.902***
	(0.696)	(0.513)	(0.616)	(0.844)	(0.678)	(0.425)	(0.561)	(0.961)
All children are female	0.047	0.130**	-0.166	0.148*	0.108	0.024	-0.064	-0.032
	(0.075)	(0.060)	(0.110)	(0.089)	(0.081)	(0.060)	(0.119)	(0.119)
Wealth index	-0.696	-0.583*	0.996	-0.875	-0.157	0.251	-0.637	0.950
	(0.435)	(0.334)	(0.777)	(0.680)	(0.543)	(0.390)	(0.839)	(0.758)
Household owned any livestock in the past 12 months	0.025	0.037	-0.151	0.115	0.154	0.006	0.067	-0.155
	(0.099)	(0.098)	(0.181)	(0.154)	(0.151)	(0.115)	(0.201)	(0.198)
Monthly expenditure in food items per capita	-0.000	-0.001	0.002*	0.000	-0.001	-0.000	-0.000	0.003*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Mom age at Round 1	0.002	-0.011	0.001	0.002	0.020**	0.015**	-0.016	-0.013
	(0.008)	(0.007)	(0.014)	(0.013)	(0.010)	(0.007)	(0.013)	(0.013)
Caregiver years of education at Round 1	0.005	0.037***	0.019	-0.047***	0.008	-0.001	0.037*	-0.008
	(0.011)	(0.009)	(0.020)	(0.017)	(0.015)	(0.011)	(0.021)	(0.018)
Head of household is female	-0.027	-0.104	-0.108	-0.016	0.225	-0.053	0.334	-0.376
	(0.145)	(0.124)	(0.264)	(0.247)	(0.201)	(0.179)	(0.309)	(0.283)
Children attended preschool	1.351***	0.134	-0.344	-0.341	1.711***	0.725***	-0.872**	-0.569*
	(0.410)	(0.213)	(0.312)	(0.469)	(0.355)	(0.146)	(0.386)	(0.338)
Child speaks Spanish	0.143	-0.209	0.125	-0.018	0.229	0.168	-0.236	-0.561*
	(0.265)	(0.198)	(0.245)	(0.257)	(0.237)	(0.129)	(0.304)	(0.330)
Child religion Catholic	-0.382***	0.003	-0.220	0.235	0.114	0.251*	0.329	-0.974***
	(0.138)	(0.117)	(0.226)	(0.183)	(0.167)	(0.138)	(0.298)	(0.371)
Child religion is Other	-0.333*	-0.066	0.035	0.303	0.120	0.037	0.233	-0.621
	(0.173)	(0.127)	(0.269)	(0.230)	(0.176)	(0.151)	(0.331)	(0.379)
Child ethnicity is White	-0.309	-0.115	0.641	-0.075	-0.785**	-0.362	1.093*	-0.744
	(0.295)	(0.163)	(0.417)	(0.374)	(0.366)	(0.264)	(0.653)	(0.601)
Child ethnicity is Mestizo	-0.305	-0.073	0.423	0.231	-1.010***	-0.267	0.758	-0.733
	(0.268)	(0.133)	(0.366)	(0.350)	(0.320)	(0.203)	(0.621)	(0.550)
Child lived at Coast	0.134	0.127	-0.677	0.603**	0.079	0.073	-0.069	0.325
	(0.303)	(0.208)	(0.451)	(0.305)	(0.369)	(0.219)	(0.657)	(0.449)
Child lived at Mountain	0.140	0.103	0.093	0.361	0.067	-0.093	-0.449	0.559
	(0.237)	(0.171)	(0.418)	(0.305)	(0.323)	(0.164)	(0.646)	(0.450)
Child lived Urban area	-0.236*	-0.072	0.223	0.358**	-0.322**	-0.018	-0.071	0.212
	(0.141)	(0.119)	(0.188)	(0.182)	(0.156)	(0.099)	(0.223)	(0.225)
Year gap between siblings (gap=1)					-0.128	0.134	-0.153	-0.250
					(0.288)	(0.220)	(0.504)	(0.383)
Year gap between siblings (gap=2)	-0.287	0.013	0.334	-0.713**	-0.078	0.059	0.106	-0.346
	(0.276)	(0.221)	(0.276)	(0.324)	(0.242)	(0.211)	(0.425)	(0.353)
Year gap between siblings (gap=3)	-0.206	-0.092	0.181	-0.164	-0.027	0.072	-0.138	-0.392
	(0.284)	(0.219)	(0.264)	(0.321)	(0.225)	(0.206)	(0.448)	(0.318)
Year gap between siblings (gap=4)	-0.045	-0.011	0.007	-0.108	-0.112	0.004	0.042	-0.262
	(0.273)	(0.213)	(0.263)	(0.343)	(0.226)	(0.209)	(0.425)	(0.337)
Year gap between siblings (gap=5)	-0.281	-0.002	0.266	-0.358	-0.056	-0.101	-0.170	-0.269
	(0.281)	(0.207)	(0.250)	(0.307)	(0.260)	(0.221)	(0.446)	(0.364)
Year gap between siblings (gap=6)	-0.230	-0.057	0.224	-0.220	-0.174	-0.146	-0.243	-0.154
	(0.277)	(0.205)	(0.245)	(0.310)	(0.263)	(0.227)	(0.447)	(0.341)
Year gap between siblings (gap=7)	-0.264	-0.112	0.461*	-0.401	-0.173	-0.067	0.083	-0.395
	(0.275)	(0.213)	(0.254)	(0.318)	(0.279)	(0.230)	(0.461)	(0.356)

	2 siblings				3 siblings			
	Hrs/day at school	*Hrs/day studying outside school*	*Hrs/day in leisure*	*Hrs/day in child-work*	*Hrs/day at school*	*Hrs/day studying outside school*	*Hrs/day in leisure*	*Hrs/day in child-work*
	(Ia)	(IIa)	(IIIa)	(IVa)	(Ib)	(IIb)	(IIIb)	(IVb)
Year gap between siblings (gap=8)	-0.343 (0.276)	-0.004 (0.219)	0.619** (0.284)	-0.751** (0.321)	-0.005 (0.258)	0.034 (0.227)	0.228 (0.445)	-0.575 (0.353)
Year gap between siblings (gap=9)	-0.239 (0.283)	-0.137 (0.229)	0.316 (0.306)	-0.529 (0.340)	-0.167 (0.250)	-0.007 (0.229)	0.062 (0.479)	-0.280 (0.418)
Year gap between siblings (gap=10)	-0.288 (0.298)	0.240 (0.222)	0.270 (0.323)	-0.938*** (0.334)	-0.128 (0.265)	-0.042 (0.241)	0.112 (0.479)	-0.155 (0.389)
Year gap between siblings (gap=11)	0.065 (0.311)	0.172 (0.242)	0.100 (0.312)	-0.685** (0.330)	-0.077 (0.411)	-0.057 (0.280)	0.160 (0.626)	-0.354 (0.607)
Year gap between siblings (gap=12)	-0.083 (0.367)	-0.077 (0.363)	-0.592 (0.479)	0.263 (0.368)	-0.646 (0.549)	-0.159 (0.335)	-0.490 (0.508)	0.025 (0.418)
Year gap between siblings (gap=13)	0.722 (0.483)	0.340 (0.393)	-0.189 (0.517)	-0.324 (0.470)	-0.617 (0.401)	-0.050 (0.233)	1.056* (0.565)	0.046 (0.392)
Year gap between siblings (gap=14)	-0.632** (0.302)	0.175 (0.245)	0.091 (0.342)	0.601 (0.385)				
Year gap between siblings (gap=15)	-0.371 (0.328)	0.044 (0.252)	-1.425*** (0.376)	1.641*** (0.375)				
Year gap between siblings (gap=26)	-1.633*** (0.339)	0.997*** (0.254)	1.122*** (0.378)	-0.935** (0.406)				
Family cluster-mean: Head of household is female	-0.390** (0.199)	-0.007 (0.180)	0.294 (0.330)	0.295 (0.303)	-0.698** (0.297)	-0.166 (0.219)	-0.424 (0.478)	0.802** (0.407)
Family cluster-mean: wealth index	1.545*** (0.486)	0.495 (0.444)	-0.966 (0.826)	0.027 (0.695)	0.545 (0.617)	-0.168 (0.447)	0.784 (0.955)	-1.432 (0.920)
Family cluster-mean: HH owned livestock past 12 months	-0.147 (0.148)	-0.152 (0.142)	0.204 (0.236)	0.270 (0.200)	-0.218 (0.199)	-0.316** (0.161)	-0.269 (0.303)	0.573** (0.285)
Family cluster-mean: Food expenditure per capita	0.001 (0.001)	0.001 (0.001)	-0.002 (0.002)	0.000 (0.001)	0.002 (0.002)	0.000 (0.001)	-0.001 (0.002)	-0.004* (0.003)
Observations (children-data points)	1,076	1,076	1,076	1,076	1,035	1,035	1,035	1,035
Observations (children)	599	599	599	599	583	583	583	583
Observations (families)	386	386	386	386	272	272	272	272
p-value $H_0: \beta_1 = \beta_2 = 0 \mid \beta_1 = \beta_2 = \beta_3 = 0$	0.132	0.28	0.063	0.000	0.496	0.603	0.015	0.000
p-value $H_0: \pi = 0$	0.000	0.231	0.292	0.59	0.060	0.354	0.705	0.001
R-squared	0.301	0.209	0.272	0.367	0.350	0.226	0.301	0.413

***p<0.001, **p<0.01, *p<0.05. Clustered robust standard errors at the family level in parentheses. Each column presents a separate regression.

Table C8. Sensitivity CRE: Family Size child work disaggregated

	2 siblings				3 siblings			
	Hrs/day at school	*Hrs/day studying outside school*	*Hrs/day in leisure*	*Hrs/day in child-work*	*Hrs/day at school*	*Hrs/day studying outside school*	*Hrs/day in leisure*	*Hrs/day in child-work*
	(Ia)	(IIa)	(IIIa)	(IVa)	(Ib)	(IIb)	(IIIb)	(IVb)
Birth order (*j* =2)	-0.787***	0.028	0.070	0.011	-0.348***	0.021	0.039	0.154**
	(0.062)	(0.055)	(0.071)	(0.039)	(0.075)	(0.051)	(0.059)	(0.076)
Birth order (*j* =3)					-0.789***	-0.061	0.049	0.147*
					(0.090)	(0.070)	(0.090)	(0.075)
Age in years (age=5)	-0.030	0.226*	-0.019	-0.046	-0.020	0.044	-0.107	0.006
	(0.076)	(0.117)	(0.090)	(0.077)	(0.074)	(0.091)	(0.081)	(0.044)
Age in years (age=6)	-0.040	0.396***	-0.021	-0.058	0.027	0.299***	-0.010	0.023
	(0.082)	(0.143)	(0.095)	(0.085)	(0.093)	(0.104)	(0.078)	(0.047)
Age in years (age=7)	-0.165**	0.456***	0.192**	-0.092	0.028	0.475***	0.108*	0.072
	(0.070)	(0.092)	(0.088)	(0.088)	(0.083)	(0.075)	(0.063)	(0.046)
Age in years (age=8)	-0.029	0.435***	0.173**	-0.075	0.055	0.526***	0.163**	0.060
	(0.069)	(0.093)	(0.081)	(0.094)	(0.083)	(0.082)	(0.071)	(0.043)
Age in years (age=9)	0.253*	0.984***	0.241	-0.003	0.309**	0.697***	0.190**	0.085
	(0.147)	(0.204)	(0.157)	(0.078)	(0.138)	(0.108)	(0.082)	(0.060)
Age in years (age=10)	-0.335**	0.402**	0.141	-0.057	0.103	0.863***	0.366***	0.094
	(0.152)	(0.178)	(0.117)	(0.088)	(0.163)	(0.126)	(0.125)	(0.073)
Age in years (age=11)	0.430***	0.892***	0.384***	-0.034	0.350***	0.835***	0.300***	0.154**
	(0.093)	(0.102)	(0.123)	(0.095)	(0.106)	(0.084)	(0.093)	(0.077)
Age in years (age=12)	0.120	0.760***	0.226**	-0.004	0.313***	0.811***	0.321***	0.132**
	(0.093)	(0.105)	(0.102)	(0.114)	(0.109)	(0.093)	(0.096)	(0.065)
Age in years (age=13)	-0.088	0.923***	0.422**	0.190	0.268	1.007***	0.343**	0.181*
	(0.240)	(0.171)	(0.200)	(0.197)	(0.189)	(0.146)	(0.155)	(0.106)
Age in years (age=14)	0.313	1.259***	0.197	0.010	0.821***	0.935***	0.374*	0.302*
	(0.308)	(0.214)	(0.140)	(0.121)	(0.207)	(0.172)	(0.226)	(0.156)
Age in years (age=15)	0.012	1.486***	0.215	-0.147	0.441	0.998***	0.895***	0.884**
	(0.294)	(0.459)	(0.289)	(0.585)	(0.270)	(0.212)	(0.323)	(0.441)
Age in years (age=16)	-0.034	1.170***	0.454*	0.278	0.157	1.138***	0.414*	1.120*
	(0.262)	(0.253)	(0.242)	(0.311)	(0.181)	(0.214)	(0.223)	(0.588)
Age in years (age=17)	-0.077	1.002***	1.049**	0.639	0.083	0.866***	0.533	2.270**
	(0.276)	(0.271)	(0.532)	(0.441)	(0.263)	(0.216)	(0.430)	(1.024)
All children are female	0.098**	0.066	-0.011	-0.047**	0.094	0.038	-0.094*	-0.109*
	(0.046)	(0.048)	(0.044)	(0.024)	(0.061)	(0.048)	(0.052)	(0.065)
Wealth index	-0.387	-0.402	-0.251	0.233	0.619*	0.479	-0.187	-0.083
	(0.323)	(0.309)	(0.348)	(0.144)	(0.343)	(0.310)	(0.376)	(0.578)
Household owned any livestock in the past 12 months	0.044	0.010	0.114	-0.043	0.046	-0.049	0.058	-0.226
	(0.076)	(0.085)	(0.075)	(0.032)	(0.100)	(0.102)	(0.059)	(0.192)
Monthly expenditure in food items per capita	-0.001**	0.001	0.001	-0.001	0.001	-0.000	0.000	0.001
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Mom age at Round 1	-0.001	0.007	-0.002	-0.002	0.003	-0.003	-0.008	-0.002
	(0.005)	(0.006)	(0.007)	(0.004)	(0.007)	(0.006)	(0.006)	(0.005)
Caregiver years of education at Round 1	-0.010	-0.015**	-0.016*	-0.001	-0.008	0.005	0.003	-0.011
	(0.009)	(0.007)	(0.009)	(0.003)	(0.009)	(0.009)	(0.008)	(0.007)
Head of household is female	0.025	-0.042	-0.073	0.039	-0.314**	-0.109	-0.095	0.279
	(0.112)	(0.109)	(0.130)	(0.056)	(0.129)	(0.148)	(0.121)	(0.238)
Children attended preschool	-0.101	0.001	-0.374	0.072	-0.055	0.140	-0.436**	-0.152
	(0.111)	(0.148)	(0.328)	(0.057)	(0.136)	(0.115)	(0.162)	(0.195)
Child speaks Spanish	0.047	0.012	0.010	-0.209	-0.044	-0.368**	0.013	-0.057
	(0.145)	(0.146)	(0.161)	(0.179)	(0.149)	(0.145)	(0.187)	(0.158)
Child religion Catholic	0.104	0.144	0.018	-0.046	-0.252	-0.142	-0.056	-0.439
	(0.098)	(0.115)	(0.079)	(0.056)	(0.194)	(0.108)	(0.113)	(0.311)
Child religion is Other	0.179	0.320**	-0.124	-0.093	-0.172	0.051	-0.041	-0.375
	(0.115)	(0.141)	(0.101)	(0.069)	(0.201)	(0.117)	(0.125)	(0.286)

	2 siblings				3 siblings			
	Hrs/day at school	*Hrs/day studying outside school*	*Hrs/day in leisure*	*Hrs/day in child-work*	*Hrs/day at school*	*Hrs/day studying outside school*	*Hrs/day in leisure*	*Hrs/day in child-work*
	(Ia)	(IIa)	(IIIa)	(IVa)	(Ib)	(IIb)	(IIIb)	(IVb)
Child ethnicity is White	0.064 (0.138)	0.094 (0.226)	-0.110 (0.156)	-0.053 (0.074)	-0.725*** (0.269)	-0.359* (0.205)	0.439* (0.255)	-0.168 (0.189)
Child ethnicity is Mestizo	0.121 (0.116)	0.295 (0.207)	-0.108 (0.156)	-0.050 (0.076)	-0.749*** (0.238)	-0.377** (0.181)	0.506** (0.254)	-0.200 (0.190)
Child lived at Coast	0.337** (0.143)	0.059 (0.172)	0.069 (0.134)	0.052 (0.047)	0.193 (0.213)	0.245 (0.208)	-0.208 (0.198)	0.061 (0.116)
Child lived at Mountain	0.101 (0.134)	-0.179 (0.133)	0.302 (0.240)	0.040 (0.080)	0.268 (0.199)	0.138 (0.153)	-0.077 (0.207)	0.150 (0.117)
Child lived Urban area	0.176** (0.089)	-0.146* (0.077)	0.179 (0.122)	0.083* (0.045)	0.113 (0.121)	0.260*** (0.095)	-0.132 (0.118)	-0.083 (0.084)
Year gap between siblings (gap=1)					-0.284 (0.197)	-0.503*** (0.174)	0.361** (0.170)	0.211 (0.168)
Year gap between siblings (gap=2)	-0.161 (0.126)	-0.074 (0.172)	-0.297** (0.137)	-0.031 (0.052)	-0.296* (0.178)	-0.451*** (0.169)	0.105 (0.144)	0.262* (0.157)
Year gap between siblings (gap=3)	-0.059 (0.130)	0.128 (0.160)	-0.059 (0.150)	0.020 (0.074)	-0.205 (0.159)	-0.464*** (0.162)	0.070 (0.141)	0.183 (0.183)
Year gap between siblings (gap=4)	0.017 (0.146)	0.038 (0.162)	-0.103 (0.153)	0.072 (0.090)	-0.323* (0.174)	-0.498*** (0.170)	0.131 (0.142)	0.420** (0.198)
Year gap between siblings (gap=5)	-0.009 (0.135)	0.040 (0.151)	-0.131 (0.145)	-0.098** (0.046)	-0.151 (0.184)	-0.356** (0.180)	0.187 (0.171)	0.021 (0.175)
Year gap between siblings (gap=6)	0.024 (0.134)	-0.057 (0.153)	0.003 (0.146)	-0.048 (0.040)	-0.217 (0.198)	-0.347* (0.181)	0.132 (0.143)	0.303* (0.171)
Year gap between siblings (gap=7)	-0.093 (0.140)	0.036 (0.161)	-0.133 (0.138)	-0.064 (0.042)	-0.300* (0.175)	-0.382** (0.191)	0.115 (0.144)	0.209 (0.151)
Year gap between siblings (gap=8)	-0.260* (0.149)	-0.046 (0.161)	-0.195 (0.141)	-0.059 (0.043)	-0.445** (0.196)	-0.589*** (0.193)	0.188 (0.159)	0.216 (0.150)
Year gap between siblings (gap=9)	-0.338** (0.155)	0.093 (0.161)	-0.137 (0.144)	0.051 (0.069)	-0.348 (0.252)	-0.371* (0.215)	0.185 (0.182)	0.240 (0.158)
Year gap between siblings (gap=10)	-0.461*** (0.139)	0.002 (0.173)	-0.310** (0.137)	-0.017 (0.053)	-0.368* (0.218)	-0.449** (0.210)	0.474** (0.208)	0.203 (0.168)
Year gap between siblings (gap=11)	-0.297** (0.147)	-0.039 (0.172)	-0.098 (0.151)	-0.036 (0.046)	-0.403* (0.227)	-0.086 (0.372)	-0.020 (0.196)	0.055 (0.154)
Year gap between siblings (gap=12)	-0.307 (0.236)	0.177 (0.266)	0.552 (0.377)	0.005 (0.050)	-0.226 (0.300)	0.121 (0.211)	0.091 (0.144)	0.122 (0.185)
Year gap between siblings (gap=13)	-0.214 (0.163)	0.275 (0.260)	-0.332* (0.186)	-0.021 (0.084)	0.186 (0.190)	-0.701*** (0.164)	0.226 (0.217)	0.301* (0.180)
Year gap between siblings (gap=14)	-0.114 (0.165)	0.590*** (0.195)	-0.248 (0.172)	0.097 (0.082)				
Year gap between siblings (gap=15)	-0.164 (0.168)	0.469** (0.205)	1.479*** (0.152)	0.013 (0.060)				
Year gap between siblings (gap=26)	0.152 (0.171)	-0.683*** (0.210)	-0.283* (0.167)	0.095 (0.076)				
Family cluster-mean: Head of household is female	0.080 (0.146)	0.060 (0.142)	0.186 (0.171)	-0.001 (0.086)	0.350* (0.193)	0.140 (0.185)	0.153 (0.179)	-0.090 (0.211)
Family cluster-mean: wealth index	0.196 (0.361)	0.135 (0.326)	-0.019 (0.405)	-0.353* (0.199)	-0.823** (0.398)	-0.595 (0.380)	0.055 (0.443)	0.155 (0.697)
Family cluster-mean: HH owned livestock past 12 months	0.007 (0.093)	0.028 (0.109)	0.110 (0.109)	0.070* (0.036)	0.021 (0.143)	0.123 (0.150)	0.213** (0.103)	0.217 (0.186)

	2 siblings				3 siblings			
	Hrs/day at school	*Hrs/day studying outside school*	*Hrs/day in leisure*	*Hrs/day in child-work*	*Hrs/day at school*	*Hrs/day studying outside school*	*Hrs/day in leisure*	*Hrs/day in child-work*
	(Ia)	(IIa)	(IIIa)	(IVa)	(Ib)	(IIb)	(IIIb)	(IVb)
Family cluster-mean: Food expenditure per capita	0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	0.001 (0.001)	-0.002 (0.001)
Observations (children-data points)	1,076	1,076	1,076	1,076	1,035	1,035	1,035	1,035
Observations (children)	599	599	599	599	583	583	583	583
Observations (families)	386	386	386	386	272	272	272	272
p-value $H_0: \beta_1 = \beta_2 = 0 \mid \beta_1 = \beta_2 = \beta_3 = 0$	0	0.607	0.324	0.784	0	0.239	0.805	0.118
p-value $H_0: \pi = 0$	0.579	0.817	0.495	0.326	0.075	0.1	0.273	0.225
R-squared	0.327	0.253	0.18	0.094	0.256	0.304	0.278	0.22

***p<0.001, **p<0.01, *p<0.05. Clustered robust standard errors at the family level in parentheses. Each column presents a separate regression.

Table C9. Sensitivity CRE: birthweight and PPVT score

	Birthweight and PPVT score			Mom age (28+) and birthweight		
	Hrs/day at school (I)	*Hrs/day in leisure* (II)	*Hrs/day in care* (III)	*Hrs/day at school* (IV)	*Hrs/day in leisure* (V)	*Hrs/day in care* (VI)
Birth order (j =2)	-0.124* (0.075)	0.271** (0.131)	-0.773*** (0.061)	-0.380** (0.176)	0.173 (0.315)	-0.481*** (0.107)
Round (round=4)	2.793*** (0.832)	7.078*** (1.063)	0.703* (0.420)	9.608*** (1.935)	4.536 (3.786)	-0.086 (0.232)
Age in years (age=5)	1.413*** (0.456)	-1.128** (0.526)	-0.020 (0.118)	-0.994** (0.480)	-0.529 (0.840)	-0.063 (0.320)
Age in years (age=6)	1.449*** (0.473)	-1.189** (0.594)	-0.028 (0.142)	1.273*** (0.456)	-2.822*** (0.893)	-0.174 (0.447)
Age in years (age=7)	1.975*** (0.373)	-2.077*** (0.451)	-0.119 (0.099)	0.388 (0.313)	-2.593*** (0.593)	-0.083 (0.205)
Age in years (age=8)	1.994*** (0.374)	-2.270*** (0.464)	-0.033 (0.088)	0.289 (0.318)	-2.773*** (0.543)	-0.002 (0.207)
Age in years (age=9)	2.465*** (0.449)	-2.446*** (0.566)	0.161 (0.166)	0.026 (0.607)	-3.854*** (1.116)	-0.068 (0.449)
Age in years (age=10)	2.285*** (0.476)	-1.936*** (0.625)	-0.171 (0.190)	-0.040 (0.638)	-3.535*** (1.317)	-0.274 (0.462)
Age in years (age=11)	2.198*** (0.424)	-2.877*** (0.514)	0.343** (0.154)	-0.256 (0.525)	-3.233*** (0.933)	0.258 (0.400)
Age in years (age=12)	2.385*** (0.429)	-2.888*** (0.530)	0.090 (0.151)	0.103 (0.538)	-3.864*** (0.888)	0.140 (0.403)
Child is female	0.055 (0.065)	-0.163 (0.104)	0.003 (0.050)	-0.188 (0.134)	-0.290 (0.256)	0.094 (0.062)
Wealth index	-0.717 (0.436)	1.121 (0.785)	-0.340 (0.348)	-1.664* (1.010)	2.870 (2.005)	-0.754 (0.550)
Household owned any livestock in the past 12 months	0.017 (0.096)	-0.065 (0.179)	0.080 (0.074)	0.087 (0.195)	-0.401 (0.354)	0.051 (0.089)
Monthly expenditure in food items per capita	-0.001 (0.001)	0.004*** (0.001)	-0.000 (0.000)	-0.001 (0.001)	0.001 (0.001)	0.000 (0.000)
Mom age at Round 1 (YL child age~)	-0.002 (0.009)	0.003 (0.014)	0.000 (0.006)	-0.030 (0.025)	-0.009 (0.046)	-0.003 (0.009)

	Birthweight and PPVT score			**Mom age (28+) and birthweight**		
	Hrs/day at school (I)	*Hrs/day in leisure* (II)	*Hrs/day in care* (III)	*Hrs/day at school* (IV)	*Hrs/day in leisure* (V)	*Hrs/day in care* (VI)
Caregiver years of education at Round 1	0.005	0.027	-0.008	0.036	-0.098**	0.013
	(0.012)	(0.022)	(0.009)	(0.027)	(0.049)	(0.011)
Head of household is female	-0.002	0.053	-0.028	-0.324	-1.367**	-0.063
	(0.135)	(0.258)	(0.119)	(0.220)	(0.663)	(0.352)
Children attended preschool	0.573	0.123	0.036	-0.093	-0.660	-0.355
	(0.370)	(0.297)	(0.093)	(0.462)	(0.902)	(0.262)
Child speaks Spanish	0.084	0.285	-0.180	-0.919	1.828*	-0.579***
	(0.247)	(0.348)	(0.160)	(0.597)	(1.054)	(0.191)
Child religion Catholic	-0.330**	-0.124	0.028	0.041	-0.644	-0.152
	(0.140)	(0.229)	(0.116)	(0.256)	(0.480)	(0.111)
Child religion is Other	-0.384**	-0.035	0.189	-0.541	0.595	-0.129
	(0.167)	(0.290)	(0.141)	(0.506)	(0.896)	(0.200)
Child ethnicity is White	-0.429	0.899**	-0.077	-2.050***	3.847***	-0.020
	(0.266)	(0.434)	(0.164)	(0.440)	(1.090)	(0.259)
Child ethnicity is Mestizo	-0.335	0.602	0.034	-2.485***	3.847***	0.171
	(0.245)	(0.395)	(0.152)	(0.416)	(1.108)	(0.273)
Child lived at Coast	0.490**	-0.929**	0.169	0.463	1.292**	0.065
	(0.228)	(0.451)	(0.168)	(0.370)	(0.600)	(0.292)
Child lived at Mountain	-0.075	-0.138	0.116	-0.277	2.037***	0.253
	(0.182)	(0.447)	(0.150)	(0.347)	(0.593)	(0.206)
Child lived Urban area	-0.161	0.192	0.146	-1.407***	0.414	0.318**
	(0.133)	(0.195)	(0.101)	(0.436)	(0.681)	(0.140)
Year gap between siblings (gap=2)	-0.247	0.100	-0.082	1.017*	-1.887***	-0.329
	(0.202)	(0.286)	(0.117)	(0.524)	(0.720)	(0.459)
Year gap between siblings (gap=3)	-0.154	0.080	-0.077	0.512	-1.606**	-0.221
	(0.206)	(0.304)	(0.126)	(0.492)	(0.741)	(0.438)
Year gap between siblings (gap=4)	-0.086	-0.243	0.147	0.717	-2.039***	-0.112
	(0.205)	(0.296)	(0.148)	(0.462)	(0.745)	(0.462)
Year gap between siblings (gap=5)	-0.254	0.042	0.028	0.759	-1.608**	-0.259
	(0.218)	(0.300)	(0.128)	(0.489)	(0.785)	(0.480)
Year gap between siblings (gap=6)	-0.159	0.007	0.055	1.034*	-1.572*	-0.295
	(0.207)	(0.287)	(0.121)	(0.543)	(0.846)	(0.443)
Year gap between siblings (gap=7)	-0.211	0.263	-0.045	0.913*	-1.179*	-0.410
	(0.206)	(0.303)	(0.134)	(0.504)	(0.704)	(0.443)
Year gap between siblings (gap=8)	-0.336	0.400	-0.187	0.849	-1.182	-0.207
	(0.213)	(0.339)	(0.146)	(0.542)	(0.888)	(0.452)
Year gap between siblings (gap=9)	-0.456*	0.334	-0.232	-0.031	0.385	-0.184
	(0.238)	(0.382)	(0.148)	(0.554)	(0.909)	(0.497)
Year gap between siblings (gap=10)	-0.281	0.009	-0.408***	1.303**	-2.764***	-0.383
	(0.257)	(0.391)	(0.135)	(0.664)	(0.938)	(0.483)
Year gap between siblings (gap=11)	-0.003	-0.145	-0.234	1.142**	-1.944**	-0.183
	(0.257)	(0.351)	(0.145)	(0.535)	(0.917)	(0.449)
Year gap between siblings (gap=12)	-0.071	-0.693	-0.263	0.994	-2.316*	-0.389
	(0.329)	(0.564)	(0.229)	(0.627)	(1.240)	(0.442)
Year gap between siblings (gap=13)	0.674*	-0.176	-0.163	1.808***	-2.716***	-0.341
	(0.402)	(0.547)	(0.154)	(0.550)	(1.022)	(0.446)
Year gap between siblings (gap=14)	-0.582**	0.151	-0.051	1.302**	-1.360	-0.627
	(0.240)	(0.384)	(0.164)	(0.595)	(0.969)	(0.470)
Year gap between siblings (gap=15)	-0.101	-1.438***	-0.299*	1.277*	-4.077***	-0.280
	(0.251)	(0.403)	(0.174)	(0.750)	(1.175)	(0.478)
Year gap between siblings (gap=26)	-1.490***	0.585	0.253	0.123	-0.489	0.119
	(0.280)	(0.431)	(0.190)	(0.594)	(1.106)	(0.464)
Family cluster-mean: Head of household is female	-0.151	-0.070	0.007	-0.155	1.522*	0.010
	(0.179)	(0.340)	(0.148)	(0.320)	(0.814)	(0.389)
Family cluster-mean: wealth index	1.297***	-1.415*	0.179	3.295**	-1.208	0.522
	(0.486)	(0.814)	(0.392)	(1.285)	(2.433)	(0.561)

	Birthweight and PPVT score			Mom age (28+) and birthweight		
	Hrs/day at school (I)	*Hrs/day in leisure* (II)	*Hrs/day in care* (III)	*Hrs/day at school* (IV)	*Hrs/day in leisure* (V)	*Hrs/day in care* (VI)
Family cluster-mean: HH owned livestock past 12 months	-0.097	0.125	-0.086	-0.466*	0.432	-0.054
	(0.144)	(0.224)	(0.091)	(0.258)	(0.539)	(0.145)
Family cluster-mean: Food expenditure per capita	0.001	-0.003**	0.000	0.003**	-0.006*	-0.001*
	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)	(0.001)
Birthweight (grams)	0.000**	-0.000*	-0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Standardised Age-Adj PPVT score	0.088*	-0.132*	-0.003			
	(0.048)	(0.072)	(0.035)			
Observations (children-data points)	955	955	955	265	265	265
Observations (children)	493	493	493	137	137	137
Observations (families)	426	426	426	126	126	126
p-value $H_0: \beta_1 = \beta_2 = 0$	0.099	0.039	0.000	0.03	0.582	0.000
p-value $H_0: \pi = 0$	0.004	0.086	0.862	0.002	0.047	0.460
R-squared	0.270	0.218	0.316	0.443	0.356	0.375

***p<0.001, **p<0.01, *p<0.05. Clustered robust standard errors at the family level in parentheses. Each column presents a separate regression.

Table C10. Average Marginal Effects: Parental aspirations and birth order

	University/ Postgraduate (I)	*University/ Postgraduate* (II)
Birth order (j =2)	-0.047	-0.082
	(0.034)	(0.060)
Birth order (j =3)		-0.068
		(0.051)
Standardised Age-Adj PPVT score	0.057***	0.053
	(0.017)	(0.043)
All children are female	-0.021	0.003
	(0.022)	(0.030)
Mom age at Round 1 (YL child age~)	0.006	0.003
	(0.003)	(0.004)
Caregiver years of education at Round 1	0.001	0.000
	(0.004)	(0.005)
Head of household is female	-0.049	0.085
	(0.036)	(0.104)
Wealth index	0.067	0.217
	(0.130)	(0.271)
Household owned any livestock in the past 12 months	-0.061	0.037
	(0.038)	(0.061)
Monthly expenditure in food items per capita	0.000	0.000
	(0.000)	(0.001)
Children attended preschool	0.080*	0.08
	(0.039)	(0.100)
Year gap between siblings (gap=2)	-0.003	0.027
	(0.046)	(0.082)
Year gap between siblings (gap=3)	-0.108	-0.02
	(0.073)	(0.085)
Year gap between siblings (gap=4)	-0.034	-0.070
	(0.056)	(0.106)
Year gap between siblings (gap=5)	-0.023	0.087
	(0.049)	(0.115)

	University/ Postgraduate (I)	*University/ Postgraduate* (II)
Year gap between siblings (gap=6)	-0.088 (0.054)	-0.047 (0.102)
Year gap between siblings (gap=7)	-0.045 (0.052)	0.077 (0.107)
Year gap between siblings (gap=8)	0.036 (0.049)	-0.045 (0.121)
Year gap between siblings (gap=9)	-0.098 (0.066)	0.064 (0.104)
Year gap between siblings (gap=10)	-0.042 (0.061)	-0.089 (0.119)
Year gap between siblings (gap=11)	-0.038 (0.064)	-0.079 (0.128)
Year gap between siblings (gap=12)	-0.186* (0.085)	-0.415* (0.201)
Year gap between siblings (gap=13)	-0.400* (0.173)	
Year gap between siblings (gap=14)	-0.716*** (0.101)	
Child speaks Spanish	-0.038 (0.070)	0.114 (0.109)
Child religion Catholic	0.066 (0.049)	-0.066 (0.139)
Child religion is Other	0.057 (0.056)	-0.037 (0.138)
Child ethnicity is White	0.116 (0.075)	-0.493 (.)
Child ethnicity is Mestizo	0.13 (0.068)	-0.544 (.)
Child lived at Coast	-0.754*** (0.143)	0.691 (0.544)
Child lived at Mountain	-0.832*** (0.107)	0.034 (0.151)
Child lived Urban area	-0.006 (0.037)	-0.011 (0.053)
Family cluster-mean: Head of household is female	0.008 (0.052)	0.009 (0.101)
Family cluster-mean: wealth index	0.088 (0.158)	0.294 (0.335)
Family cluster-mean: HH owned livestock past 12 months	0.112* (0.051)	0.008 (0.083)
Family cluster-mean: Food expenditure per capita	0.000 (0.000)	0.000 (0.001)
Observations (children-data points)	760	504

***p<0.001, **p<0.01, *p<0.05. Clustered robust standard errors at the family level in parentheses.

Table C11. CRE estimates: Joint parental aspiration and birth order

	Hrs/day at school (I)	*Hrs/day in care* (II)
Birth order (j =2)	-0.515 (0.325)	-0.742*** (0.162)
Parental Aspiration: University/Postgrad (p =1)	0.035 (0.144)	-0.046 (0.133)
Birth order (j =2)* University/Postgrad (p =1)	0.340 (0.332)	-0.010 (0.162)
Age in years (age=7)	-0.012 (0.325)	-0.023 (0.512)

	Hrs/day at school (I)	Hrs/day in care (II)
Age in years (age=8)	-0.004 (0.302)	0.130 (0.511)
Age in years (age=10)	-	0.008 (0.514)
Age in years (age=11)	-0.462 (0.362)	0.673 (0.532)
Age in years (age=12)	-0.347 (0.377)	0.404 (0.535)
All children are female	0.069 (0.072)	0.076 (0.059)
Wealth index	-0.373 (0.380)	-0.583 (0.417)
Household owned any livestock in the past 12 months	-0.017 (0.098)	0.086 (0.090)
Monthly expenditure in food items per capita	-0.001 (0.001)	-0.001* (0.001)
Mom age at Round 1 (YL child age~)	0.004 (0.008)	-0.003 (0.007)
Caregiver years of education at Round 1	0.002 (0.011)	-0.012 (0.010)
Head of household is female	0.158 (0.152)	-0.003 (0.151)
Children attended preschool	0.314 (0.410)	-0.034 (0.172)
Child speaks Spanish	0.103 (0.244)	0.089 (0.228)
Child religion Catholic	-0.399*** (0.154)	0.164 (0.138)
Child religion is Other	-0.349* (0.181)	0.218 (0.159)
Child ethnicity is White	-0.333 (0.287)	0.063 (0.158)
Child ethnicity is Mestizo	-0.307 (0.261)	0.147 (0.142)
Child lived at Coast	0.203 (0.283)	0.333* (0.196)
Child lived at Mountain	-0.150 (0.233)	0.134 (0.181)
Child lived Urban area	-0.118 (0.129)	0.234** (0.117)
Year gap between siblings (gap=2)	-0.265 (0.259)	-0.255 (0.187)
Year gap between siblings (gap=3)	-0.152 (0.259)	-0.130 (0.184)
Year gap between siblings (gap=4)	-0.143 (0.249)	-0.020 (0.206)
Year gap between siblings (gap=5)	-0.226 (0.260)	-0.120 (0.191)
Year gap between siblings (gap=6)	-0.127 (0.252)	-0.024 (0.190)
Year gap between siblings (gap=7)	-0.187 (0.252)	-0.165 (0.191)
Year gap between siblings (gap=8)	-0.366 (0.256)	-0.320 (0.198)
Year gap between siblings (gap=9)	-0.309 (0.258)	-0.359* (0.202)
Year gap between siblings (gap=10)	-0.282 (0.286)	-0.554*** (0.191)
Year gap between siblings (gap=11)	0.089 (0.287)	-0.339* (0.197)

	Hrs/day at school	*Hrs/day in care*
	(I)	(II)
Year gap between siblings (gap=12)	0.010 (0.369)	-0.381 (0.272)
Year gap between siblings (gap=13)	1.035** (0.448)	-0.330 (0.221)
Year gap between siblings (gap=14)	-0.459 (0.300)	-0.178 (0.240)
Family cluster-mean: Head of household is female	-0.491** (0.193)	0.035 (0.185)
Family cluster-mean: wealth index	0.579 (0.468)	0.432 (0.472)
Family cluster-mean: HH owned livestock past 12 months	-0.160 (0.131)	-0.002 (0.110)
Family cluster-mean: Food expenditure per capita	0.001 (0.001)	0.001 (0.001)
Standardised Age-Adj PPVT score	0.084 (0.056)	-0.020 (0.043)
Observations (children-data points)	760	760
Observations (children)	397	397
p-value $H_0: \beta_1 = \beta_2 = 0$	0.106	0.000
p-value $H_0: \pi = 0$	0.020	0.432
R-squared	0.168	0.326

***p<0.001, **p<0.01, *p<0.05. Clustered robust standard errors at the family level in parentheses. Each column presents a separate regression.

Table C12. Hausman-Taylor estimates

	Hrs/day at school	*Hrs/day in leisure*
	(I)	(II)
Birth order (j =2)	0.251 (0.306)	0.153 (0.301)
Wealth index	-0.184 (0.531)	
Monthly expenditure in food items per capita		0.003* (0.001)
Observations	1336	1336
p-value $H_0: \beta_1 = \beta_2 = 0$	0.412	0.610
p-value coef. problematic covariate[1] $= 0$	0.729	0.014

***p<0.001, **p<0.01, *p<0.05. Clustered robust standard errors at the family level in parentheses. Each column represents a separate regression.

Table C13. Hausman-Taylor estimates: Family Size

	2 siblings		**3 siblings**	
	Hrs/day at school	*Hrs/day at school*	*Hrs/day child work*	*Hrs/day in care*
	(Ia)	(Ib)	(IIb)	(IIIb)
Birth order (j =2)	0.782 (0.588)	0.099 (0.367)	-0.409 (0.484)	-0.336 (0.254)
Birth order (j =3)		-0.307 (0.920)	-0.594 (1.555)	-0.891 (0.427)
Head of household is female	-0.072 (0.200)	0.387 (0.214)	-0.591 (0.322)	
Wealth index	-0.227 (0.576)			0.639 (0.495)

	2 siblings		3 siblings	
	Hrs/day at school	*Hrs/day at school*	*Hrs/day child work*	*Hrs/day in care*
	(Ia)	(Ib)	(IIb)	(IIIb)
Household owned any livestock in the past 12 months			-0.193 (0.232)	
Observations	1076	1035	1035	1035
p-value $H_0: \beta_1 = \beta_2 = 0 \mid \beta_1 = \beta_2 = \beta_3 = 0$	0.183	0.788	0.699	0.090
p-value $H_0: \pi = 0$	0.881	0.071	0.153	0.197

***p<0.001, **p<0.01, *p<0.05. Clustered robust standard errors at the family level in parentheses. Each column represents a separate regression.

Table C14. Hausman-Taylor estimates: birthweight, PPVT score, & mother's age

	Birthweight and PPVT score		Mom age (28+) and birthweight	
	Hrs/day at school	*Hrs/day in leisure*	*Hrs/day at school*	*Hrs/day in leisure*
	(Ia)	(IIa)	(Ib)	(IIb)
Birth order (j =2)	-0.424 (0.610)	1.551* (0.934)	-0.765 (0.995)	0.336 (1.498)
Wealth index	-0.414 (0.605)		-1.214 (1.239)	
Monthly expenditure in food items per capita		0.004** (0.002)	-0.001 (0.001)	0.001 (0.002)
Head of household is female				-1.632 (1.069)
Observations	955	955	265	265
p-value $H_0: \beta_1 = \beta_2 = 0$	0.488	0.097	0.442	0.822
p-value $H_0: \pi = 0$	0.494	0.033	0.428	0.246

***p<0.001, **p<0.01, *p<0.05. Clustered robust standard errors at the family level in parentheses. Each column presents a separate regression. Each column represents a separate regression.

Table C15. Random Effects estimates

	Hrs/day at school	*Hrs/day studying outside school*	*Hrs/day in leisure*	*Hrs/day in child-work*
	(I)	(II)	(III)	(IV)
Birth order (j =2)	-0.130* (0.072)	0.063 (0.062)	0.348*** (0.119)	-0.810*** (0.103)
Age in years (age=5)	0.980*** (0.225)	0.230* (0.129)	-0.741** (0.288)	0.126 (0.171)
Age in years (age=6)	1.211*** (0.254)	0.716*** (0.173)	-1.269*** (0.313)	0.249 (0.195)
Age in years (age=7)	1.553*** (0.187)	0.696*** (0.108)	-1.575*** (0.232)	0.425*** (0.160)
Age in years (age=8)	1.589*** (0.187)	0.757*** (0.108)	-1.791*** (0.240)	0.455*** (0.141)
Age in years (age=9)	1.815*** (0.217)	1.109*** (0.194)	-2.198*** (0.285)	1.154*** (0.259)
Age in years (age=10)	1.593*** (0.264)	1.138*** (0.157)	-1.564*** (0.445)	0.204 (0.268)
Age in years (age=11)	1.651*** (0.184)	0.935*** (0.125)	-2.476*** (0.253)	1.590*** (0.182)
Age in years (age=12)	1.849*** (0.194)	1.178*** (0.130)	-2.518*** (0.261)	0.989*** (0.183)

	Hrs/day at school (I)	*Hrs/day studying outside school* (II)	*Hrs/day in leisure* (III)	*Hrs/day in child-work* (IV)
Age in years (age=13)	2.218*** (0.276)	1.234*** (0.194)	-2.890*** (0.410)	1.455*** (0.364)
Age in years (age=14)	1.810*** (0.308)	1.122*** (0.238)	-2.284*** (0.487)	1.448*** (0.371)
Age in years (age=15)	1.715*** (0.360)	1.708*** (0.385)	-2.599*** (0.567)	1.118** (0.560)
Age in years (age=16)	1.315*** (0.443)	1.249*** (0.304)	-2.775*** (0.477)	2.169*** (0.645)
Age in years (age=17)	0.694 (0.694)	1.414*** (0.497)	-2.152*** (0.563)	2.866*** (0.818)
Child is female	0.075 (0.063)	0.138*** (0.049)	-0.274*** (0.091)	0.139* (0.075)
Wealth index	0.326 (0.253)	-0.110 (0.219)	0.192 (0.471)	-0.981** (0.384)
Household owned any livestock in the past 12 months	-0.054 (0.067)	-0.078 (0.067)	-0.067 (0.112)	0.185* (0.097)
Monthly expenditure in food items per capita	0.000 (0.000)	-0.000 (0.000)	0.001* (0.001)	0.000 (0.001)
Mom age at Round 1 (YL child age~)	0.001 (0.008)	-0.009 (0.006)	-0.006 (0.012)	0.015 (0.011)
Caregiver years of education at Round 1	0.019 (0.013)	0.041*** (0.008)	0.007 (0.020)	-0.047*** (0.015)
Head of household is female	-0.211** (0.087)	-0.134* (0.078)	0.124 (0.132)	0.126 (0.118)
Children attended preschool	1.414*** (0.409)	0.288 (0.201)	-0.792* (0.475)	-0.129 (0.419)
Child speaks Spanish	0.095 (0.292)	-0.067 (0.170)	-0.084 (0.317)	-0.172 (0.274)
Child religion Catholic	-0.295** (0.120)	-0.164 (0.131)	-0.096 (0.200)	0.112 (0.152)
Child religion is Other	-0.292* (0.152)	-0.317** (0.142)	-0.052 (0.254)	0.369* (0.205)
Child ethnicity is White	-0.316 (0.286)	-0.092 (0.155)	0.769* (0.398)	-0.033 (0.367)
Child ethnicity is Mestizo	-0.319 (0.262)	-0.166 (0.126)	0.572 (0.354)	0.253 (0.343)
Child lived at Coast	0.408 (0.277)	0.172 (0.191)	-0.917** (0.416)	0.574** (0.262)
Child lived at Mountain	0.069 (0.218)	0.297 (0.189)	-0.055 (0.402)	0.294 (0.262)
Child lived Urban area	-0.059 (0.126)	0.041 (0.110)	0.094 (0.181)	0.249 (0.165)
Year gap between siblings (gap=2)	-0.297 (0.206)	0.031 (0.150)	0.306 (0.329)	-0.530** (0.239)
Year gap between siblings (gap=3)	-0.200 (0.207)	-0.050 (0.154)	0.175 (0.309)	-0.242 (0.235)
Year gap between siblings (gap=4)	-0.020 (0.207)	-0.036 (0.156)	-0.106 (0.311)	-0.022 (0.268)
Year gap between siblings (gap=5)	-0.295 (0.216)	0.038 (0.161)	0.205 (0.316)	-0.336 (0.241)
Year gap between siblings (gap=6)	-0.177 (0.212)	0.010 (0.158)	0.083 (0.310)	-0.170 (0.240)
Year gap between siblings (gap=7)	-0.227 (0.207)	-0.057 (0.155)	0.359 (0.311)	-0.435* (0.236)
Year gap between siblings (gap=8)	-0.310 (0.208)	0.047 (0.167)	0.519 (0.344)	-0.712*** (0.244)

	Hrs/day at school (I)	Hrs/day studying outside school (II)	Hrs/day in leisure (III)	Hrs/day in child-work (IV)
Year gap between siblings (gap=9)	-0.334 (0.248)	-0.089 (0.179)	0.431 (0.394)	-0.532* (0.275)
Year gap between siblings (gap=10)	-0.256 (0.245)	0.266 (0.171)	0.231 (0.384)	-0.908*** (0.254)
Year gap between siblings (gap=11)	0.077 (0.262)	0.215 (0.207)	-0.012 (0.370)	-0.631** (0.269)
Year gap between siblings (gap=12)	-0.066 (0.321)	0.018 (0.314)	-0.537 (0.557)	0.189 (0.305)
Year gap between siblings (gap=13)	0.633 (0.414)	0.322 (0.280)	0.147 (0.567)	-0.076 (0.377)
Year gap between siblings (gap=14)	-0.445* (0.246)	0.163 (0.185)	0.121 (0.383)	0.466 (0.293)
Year gap between siblings (gap=15)	-0.312 (0.277)	0.000 (0.204)	-1.059*** (0.408)	1.265*** (0.287)
Year gap between siblings (gap=26)	-1.615*** (0.286)	1.051*** (0.208)	1.234*** (0.394)	-1.202*** (0.327)
Observations (children-data points)	1,336	1,336	1,336	1,336
Observations (children)	734	734	734	734
p-value $H_0: \beta_1 = \beta_2 = 0$	0.071	0.314	0.004	0.000

***p<0.001, **p<0.01, *p<0.05. Clustered robust standard errors at the family level in parentheses. Each column presents a separate regression.

Table C16. Random Effects estimates: child work disaggregated

	Hrs/day care (V)	Hrs/day chores (VI)	Hrs/day tasks (VII)	Hrs/day paid work (VIII)
Birth order (j =2)	-0.811*** (0.054)	0.029 (0.047)	0.005 (0.056)	-0.003 (0.024)
Age in years (age=5)	-0.014 (0.062)	0.172* (0.103)	0.007 (0.072)	-0.026 (0.062)
Age in years (age=6)	-0.049 (0.071)	0.373*** (0.126)	-0.027 (0.083)	-0.043 (0.070)
Age in years (age=7)	-0.149** (0.058)	0.467*** (0.081)	0.158** (0.070)	-0.066 (0.068)
Age in years (age=8)	-0.072 (0.053)	0.439*** (0.082)	0.159** (0.067)	-0.058 (0.071)
Age in years (age=9)	0.184* (0.111)	0.786*** (0.145)	0.156 (0.103)	-0.009 (0.065)
Age in years (age=10)	-0.281** (0.127)	0.496*** (0.132)	0.047 (0.095)	-0.053 (0.070)
Age in years (age=11)	0.375*** (0.084)	0.885*** (0.093)	0.306*** (0.103)	-0.025 (0.073)
Age in years (age=12)	0.045 (0.084)	0.767*** (0.096)	0.142* (0.084)	0.016 (0.092)
Age in years (age=13)	-0.135 (0.208)	0.999*** (0.155)	0.481** (0.200)	0.119 (0.143)
Age in years (age=14)	0.166 (0.237)	1.086*** (0.181)	0.128 (0.132)	0.010 (0.100)
Age in years (age=15)	-0.248 (0.220)	1.208*** (0.342)	-0.017 (0.191)	-0.051 (0.365)
Age in years (age=16)	-0.092 (0.258)	1.215*** (0.235)	0.315 (0.218)	0.241 (0.276)
Age in years (age=17)	-0.151 (0.263)	1.032*** (0.266)	0.941* (0.516)	0.590 (0.435)

	Hrs/day care (V)	*Hrs/day chores* (VI)	*Hrs/day tasks* (VII)	*Hrs/day paid work* (VIII)
Child is female	0.039	0.095**	-0.005	-0.022
	(0.041)	(0.038)	(0.034)	(0.017)
Wealth index	-0.210	-0.407**	-0.336*	0.036
	(0.179)	(0.184)	(0.197)	(0.066)
Household owned any livestock in the past 12 months	0.014	0.012	0.152***	-0.008
	(0.050)	(0.052)	(0.058)	(0.021)
Monthly expenditure in food items per capita	-0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Mom age at Round 1 (YL child age~)	0.004	0.006	0.004	-0.002
	(0.004)	(0.005)	(0.005)	(0.003)
Caregiver years of education at Round 1	-0.007	-0.013*	-0.018**	-0.004
	(0.007)	(0.007)	(0.008)	(0.002)
Head of household is female	0.039	0.010	-0.001	0.039
	(0.056)	(0.056)	(0.060)	(0.034)
Children attended preschool	-0.041	0.003	-0.210	0.082*
	(0.100)	(0.146)	(0.282)	(0.049)
Child speaks Spanish	-0.050	0.013	-0.082	-0.148
	(0.110)	(0.134)	(0.176)	(0.135)
Child religion Catholic	-0.020	0.114	0.035	-0.026
	(0.086)	(0.102)	(0.079)	(0.041)
Child religion is Other	0.093	0.314**	-0.039	-0.050
	(0.106)	(0.122)	(0.092)	(0.048)
Child ethnicity is White	0.021	0.087	-0.031	-0.055
	(0.134)	(0.230)	(0.142)	(0.071)
Child ethnicity is Mestizo	0.082	0.240	-0.032	-0.032
	(0.116)	(0.214)	(0.142)	(0.072)
Child lived at Coast	0.238*	0.140	0.085	0.066
	(0.136)	(0.159)	(0.126)	(0.059)
Child lived at Mountain	0.118	-0.136	0.254	0.022
	(0.123)	(0.119)	(0.202)	(0.058)
Child lived Urban area	0.122	-0.110	0.157	0.054
	(0.086)	(0.071)	(0.113)	(0.039)
Year gap between siblings (gap=2)	-0.043	-0.121	-0.261	-0.022
	(0.095)	(0.117)	(0.167)	(0.031)
Year gap between siblings (gap=3)	0.023	-0.010	-0.183	0.027
	(0.102)	(0.114)	(0.166)	(0.042)
Year gap between siblings (gap=4)	0.125	0.008	-0.201	0.093
	(0.116)	(0.118)	(0.176)	(0.073)
Year gap between siblings (gap=5)	0.087	-0.056	-0.205	-0.062
	(0.103)	(0.111)	(0.179)	(0.041)
Year gap between siblings (gap=6)	0.144	-0.138	-0.084	-0.006
	(0.106)	(0.113)	(0.181)	(0.031)
Year gap between siblings (gap=7)	0.005	-0.064	-0.258	-0.032
	(0.112)	(0.118)	(0.163)	(0.031)
Year gap between siblings (gap=8)	-0.140	-0.134	-0.286*	-0.033
	(0.122)	(0.124)	(0.165)	(0.031)
Year gap between siblings (gap=9)	-0.193	-0.026	-0.232	0.060
	(0.132)	(0.120)	(0.169)	(0.075)
Year gap between siblings (gap=10)	-0.309***	-0.105	-0.403**	-0.006
	(0.111)	(0.133)	(0.165)	(0.038)
Year gap between siblings (gap=11)	-0.173	-0.126	-0.180	-0.008
	(0.124)	(0.135)	(0.181)	(0.032)
Year gap between siblings (gap=12)	-0.185	0.091	0.406	0.008
	(0.212)	(0.256)	(0.380)	(0.039)
Year gap between siblings (gap=13)	-0.191	0.219	-0.073	-0.010
	(0.132)	(0.196)	(0.347)	(0.056)
Year gap between siblings (gap=14)	-0.012	0.472***	-0.410**	0.039
	(0.127)	(0.147)	(0.189)	(0.041)
Year gap between siblings (gap=15)	-0.206	0.273*	1.300***	0.060
	(0.133)	(0.152)	(0.167)	(0.052)

	Hrs/day care (V)	*Hrs/day chores* (VI)	*Hrs/day tasks* (VII)	*Hrs/day paid work* (VIII)
Year gap between siblings (gap=26)	0.231	-0.810***	-0.518***	0.053
	(0.142)	(0.172)	(0.181)	(0.064)
Observations (children-data points)	1,336	1,336	1,336	1,336
Observations (children)	734	734	734	734
p-value $H_0: \beta_1 = \beta_2 = 0$	0.000	0.543	0.933	0.897

***p<0.001, **p<0.01, *p<0.05. Clustered robust standard errors at the family level in parentheses. Each column presents a separate regression.

Table C17. Sensitivity CRE: time use as percentage

	Prop. at school (V)	*Prop. studying* (VI)	*Prop. leisure* (VII)	*Prop. child work* (VIII)	*Prop. sleep* (VIII)
Birth order (*j* =2)	0.002	0.005*	0.018**	-0.032**	0.006
	(0.003)	(0.003)	(0.005)	(0.004)	(0.003)
Age in years (age=5)	0.040**	0.010	-0.036**	0.005	-0.017*
	(0.009)	(0.005)	(0.012)	(0.007)	(0.008)
Age in years (age=6)	0.054**	0.032**	-0.060**	0.012	-0.036**
	(0.011)	(0.007)	(0.013)	(0.008)	(0.008)
Age in years (age=7)	0.064**	0.030**	-0.075**	0.018**	-0.037**
	(0.008)	(0.005)	(0.010)	(0.006)	(0.006)
Age in years (age=8)	0.068**	0.033**	-0.084**	0.020**	-0.038**
	(0.008)	(0.005)	(0.010)	(0.006)	(0.006)
Age in years (age=9)	0.073**	0.046**	-0.106**	0.047**	-0.052**
	(0.010)	(0.008)	(0.011)	(0.010)	(0.008)
Age in years (age=10)	0.065**	0.049**	-0.076**	0.008	-0.045**
	(0.011)	(0.007)	(0.018)	(0.011)	(0.010)
Age in years (age=11)	0.070**	0.041**	-0.114**	0.066**	-0.060**
	(0.008)	(0.005)	(0.010)	(0.007)	(0.007)
Age in years (age=12)	0.079**	0.051**	-0.115**	0.042**	-0.056**
	(0.008)	(0.006)	(0.011)	(0.008)	(0.007)
Age in years (age=13)	0.092**	0.053**	-0.136**	0.061**	-0.068**
	(0.012)	(0.008)	(0.017)	(0.015)	(0.011)
Age in years (age=14)	0.076**	0.049**	-0.106**	0.060**	-0.076**
	(0.013)	(0.010)	(0.021)	(0.015)	(0.012)
Age in years (age=15)	0.081**	0.075**	-0.115**	0.048*	-0.082**
	(0.016)	(0.016)	(0.023)	(0.023)	(0.018)
Age in years (age=16)	0.065**	0.056**	-0.127**	0.092**	-0.085**
	(0.020)	(0.012)	(0.020)	(0.025)	(0.014)
Age in years (age=17)	0.030	0.060**	-0.101**	0.117**	-0.103**
	(0.030)	(0.020)	(0.024)	(0.032)	(0.016)
Child is female	0.001	0.005*	-0.013**	0.005	0.002
	(0.003)	(0.002)	(0.004)	(0.003)	(0.002)
Wealth index	-0.018	-0.021	0.060*	-0.027	0.008
	(0.017)	(0.012)	(0.029)	(0.024)	(0.017)
Household owned any livestock in the past 12 months	0.001	-0.003	-0.007	0.004	0.008
	(0.004)	(0.004)	(0.007)	(0.006)	(0.005)
Monthly expenditure in food items per capita	-0.000	-0.000*	0.000**	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mom age at Round 1 (YL child age~)	-0.000	-0.000*	-0.000	0.001	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Caregiver years of education at Round 1	0.001	0.002**	0.001	-0.002**	-0.001**
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
Head of household is female	0.001	-0.003	0.002	-0.002	0.001
	(0.005)	(0.005)	(0.009)	(0.009)	(0.006)
Children attended preschool	0.057**	0.011	-0.043*	-0.007	-0.015
	(0.018)	(0.009)	(0.021)	(0.017)	(0.008)
Child speaks Spanish	-0.000	-0.004	-0.002	-0.007	0.013
	(0.011)	(0.007)	(0.014)	(0.011)	(0.008)

	Prop. at school (V)	Prop. studying (VI)	Prop. leisure (VII)	Prop. child work (VIII)	Prop. sleep (VIII)
Child religion Catholic	-0.010*	-0.006	-0.000	0.005	0.012*
	(0.005)	(0.006)	(0.009)	(0.006)	(0.005)
Child religion is Other	-0.010	-0.012*	-0.000	0.016	0.008
	(0.006)	(0.006)	(0.011)	(0.008)	(0.006)
Child ethnicity is White	-0.022	-0.007	0.031	-0.003	0.000
	(0.012)	(0.007)	(0.018)	(0.015)	(0.010)
Child ethnicity is Mestizo	-0.023*	-0.010	0.019	0.008	0.005
	(0.011)	(0.005)	(0.016)	(0.014)	(0.008)
Child lived at Coast	0.012	0.004	-0.037*	0.024*	-0.002
	(0.011)	(0.008)	(0.016)	(0.011)	(0.012)
Child lived at Mountain	-0.003	0.009	-0.005	0.009	-0.008
	(0.009)	(0.008)	(0.016)	(0.010)	(0.012)
Child lived Urban area	-0.006	0.001	0.004	0.009	-0.006
	(0.005)	(0.005)	(0.007)	(0.007)	(0.005)
Year gap between siblings	-0.003	0.004	0.015	-0.022*	0.006
(gap=2)	(0.009)	(0.006)	(0.014)	(0.010)	(0.010)
Year gap between siblings	-0.002	-0.000	0.006	-0.010	0.008
(gap=3)	(0.009)	(0.007)	(0.013)	(0.010)	(0.010)
Year gap between siblings	0.007	0.002	-0.006	-0.001	-0.001
(gap=4)	(0.009)	(0.007)	(0.013)	(0.011)	(0.010)
Year gap between siblings	-0.005	0.004	0.007	-0.014	0.010
(gap=5)	(0.009)	(0.007)	(0.013)	(0.010)	(0.010)
Year gap between siblings	-0.002	0.002	0.005	-0.007	0.004
(gap=6)	(0.009)	(0.007)	(0.013)	(0.010)	(0.010)
Year gap between siblings	-0.005	-0.001	0.016	-0.018	0.010
(gap=7)	(0.009)	(0.007)	(0.013)	(0.010)	(0.011)
Year gap between siblings	-0.006	0.005	0.023	-0.030**	0.009
(gap=8)	(0.009)	(0.007)	(0.014)	(0.010)	(0.011)
Year gap between siblings	-0.004	-0.000	0.019	-0.021	0.006
(gap=9)	(0.011)	(0.008)	(0.016)	(0.011)	(0.010)
Year gap between siblings	0.000	0.016*	0.013	-0.036**	0.008
(gap=10)	(0.011)	(0.007)	(0.016)	(0.011)	(0.011)
Year gap between siblings	0.009	0.010	-0.002	-0.026*	0.008
(gap=11)	(0.011)	(0.009)	(0.015)	(0.011)	(0.011)
Year gap between siblings	0.007	0.003	-0.020	0.009	0.001
(gap=12)	(0.017)	(0.014)	(0.024)	(0.012)	(0.013)
Year gap between siblings	0.024	0.013	-0.005	-0.009	-0.018
(gap=13)	(0.020)	(0.012)	(0.021)	(0.015)	(0.018)
Year gap between siblings	-0.018	0.009	0.006	0.022	-0.019
(gap=14)	(0.011)	(0.008)	(0.016)	(0.013)	(0.011)
Year gap between siblings	-0.010	0.000	-0.041**	0.053***	-0.005
(gap=15)	(0.012)	(0.009)	(0.017)	(0.012)	(0.012)
Year gap between siblings	-0.056**	0.052**	0.060**	-0.048**	-0.007
(gap=26)	(0.012)	(0.009)	(0.016)	(0.014)	(0.012)
Family cluster-mean: Head of	-0.015	-0.003	0.005	0.011	0.003
household is female	(0.008)	(0.008)	(0.012)	(0.011)	(0.008)
Family cluster-mean: wealth	0.058**	0.023	-0.061*	-0.017	-0.008
index	(0.019)	(0.016)	(0.031)	(0.026)	(0.018)
Family cluster-mean: HH	-0.005	-0.001	0.007	0.005	-0.009
owned livestock past 12 months	(0.006)	(0.005)	(0.009)	(0.007)	(0.006)
Family cluster-mean: Food	0.000*	0.000**	-0.000*	0.000	-0.000
expenditure per capita	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations (children-data points)	1,336	1,336	1,336	1,336	1,336
Observations (children)	734	734	734	734	734
Observations (families)	458	458	458	458	458
p-value $H_0: \beta_1 = \beta_2 = 0$	0.476	0.042	0.000	0.000	0.055
p-value $H_0: \pi = 0$	0.000	0.067	0.020	0.736	0.541
R-squared	0.279	0.214	0.294	0.364	0.263

***p<0.001, **p<0.01, *p<0.05. Clustered robust standard errors at the family level in parentheses. Each column presents a separate regression.