Evaluating Early Childhood Policies: An Estimable Model of Family Child Investments

Rodrigo Azuero*

Link to latest version: http://rodrigoazuero.com/files/jmp.pdf

November 2, 2016

Abstract

There is extensive evidence suggesting that skills developed early in life have consequences for adult life outcomes. Such findings have motivated a large body of literature analyzing the production of skills in young children. Nonetheless, very little is known about how families make decisions about investments in their children. In this article, I estimate a production function of skills in young children, nested within a collective model of household behavior in a developing country context. The parameters estimated are used to simulate the effects of various policies aimed at increasing skills of children in disadvantaged households that are popular in developing countries. The results show that there are substantial disparities in the skills of poor and rich children when they are five years old. I find that, in order to close this gap in skills, it is more effective to design policies that subsidize skill-enhancing goods for children than policies providing unconditional cash transfers or childcare subsidies.

1 Introduction

Research in medicine, psychology and economics shows that the way skills are shaped during the first years of life has significant consequences for adult life outcomes[1]. This fact has motivated a large amount of research in economics aimed at understanding the skill formation process in children. The results of these studies have allowed us a better

*University of Pennsylvania. This research is partially supported by the Eunice Kennedy Shriver National Institute of Child Health and Human Development (NICHD R01HD065436) grant on "Early Child Development Programs: Effective Interventions for Human Development". I am indebted to the members of my committee, Petra Todd, Andrew Shephard and Jere Behrman, for their advice and support in developing this project. Special thanks to Aureo de Paula, Chris Flinn, Holger Sieg, Hanming Fang, Sergio Urzua, Flavio Cunha, Rossa O'Keefe-O'Donovan and Jan Tilly for their comments, which significantly improved the quality of this paper. I am grateful to the Centro Nacional de Microdatos for its support with the dataset as well as to Daniela Marshall and Alejandra Abufhele for their guidance and help with the data.

[1]For a review, see Conti and Heckman (2012)

understanding of the key inputs that promote skills in young children[2]. For instance, we know that parenting and general family environment are among the most relevant inputs in the production of skills (J. Heckman & Mosso, 2014; Schoellman, 2014).

Additionally, we know that gaps in skills between rich and poor children emerge very early in life, even before they start their formal education. Duncan and Magnuson (2013) find that differences in reading and math test scores between children in the top and bottom quartile of the income distribution are about one standard deviation when they start kindergarten in the US. Schady et al. (2015) report similar quantitative results for five Latin American countries, using a vocabulary test for children younger than five. Moreover, research in neuroscience shows that malleability of skills decreases with age Nelson and Sheridan (2011). For that reason, in order to close gaps in skills between the rich and poor population, we need to develop policies addressing this issue during early childhood.

The goal of this article is to evaluate the effects that various policy interventions have on the gaps in skills between rich and poor children. Although the literature has allowed us a better understanding of the skill production function, this is not enough to assess the effectiveness of policies aimed at improving children's skills. Families administer resources and make the relevant decisions that determine the allocation of inputs for young children. Specifically, it is important to incorporate the fact that family investments in children might react to policy interventions. To do so, I develop and estimate a skill production function nested within a collective model of household behavior using data from Chile. I evaluate the effects of cash transfers, childcare subsidies and in-kind transfers, which are transfers of goods that can be used in the skill formation process in children (for example, books, toys, puzzles, and guides about early childhood development). I find that in-kind transfers provide the most cost-efficient way to reduce the gaps in skills between rich and poor children.

This article makes a number of important contributions to the literature on family investments and child outcomes. First, there are not many papers estimating a model of household behavior where parents allocate time and money to their children in order to enhance their skills (Bernal, 2008; Del Boca, Flinn, & Wiswall, 2014, 2016; Gayle, Golan, & Soytas, 2015). This is the first paper that empirically evaluates and compares the effects that cash transfers, childcare subsidies and in-kind transfers have on the gaps in skills between rich and poor children.

[2]See, for example, Cunha, Heckman, and Schennach (2010)

Cash transfer programs have been widely implemented in developing countries. In Latin America, they constitute the largest social assistance programs, covering millions of households in countries such as Brazil and Mexico (Fiszbein, Schady, & Ferreira, 2009). Additionally, governments in both developing and developed countries have invested a large amount of resources in the provision of preschool services. In 2011, the United States federal government spent US$ 8.1 billion on Head Start, the largest childcare program in the US. In Chile, firms employing more than twenty people are required to provide childcare services to their female employees. During the last ten years, Chile has experienced a massive expansion in the number of childcare providers. Between 2006 and 2010, the network of childcare providers increased its capacity, measured as the maximum number of children for whom the system could provide coverage, by approximately 500% (Dussaillant, 2016).

By delivering in-kind transfers to families, governments can directly affect the conditions in which children develop. With cash transfers, it is not possible to guarantee that a given amount of money will be spent on goods that can actually translate into better child outcomes. However, when the transfer is done via puzzles, toys, guides about child development, or specific types of food that can improve children's nutritional status, governments can enrich the environment and thus promote skills for children. These transfers are usually implemented by governments through their early childhood development programs. Currently, the program "Chile Grows with You"[3], which is the main early childhood program in Chile, delivers a basket of goods to families for such purposes. Given the large amount of resources that governments spend on enriching childhood environments, and given the fact that events during childhood largely determine adult outcomes, it is important to understand the most cost-effective way to use these resources.

This article also contributes to the literature of household decisions and child outcomes by allowing individual family members to have different preferences. This is a point of great importance for two reasons. First, modeling household behavior through the collective approach has proven to result in better empirical predictions than the unitary framework. Second, from a policy perspective, it is common to see interventions targeting individual household members. For instance, most cash transfer programs in developing countries state as an explicit condition that, in households with children, mothers should be the sole recipients of such subsidies (Fiszbein et al., 2009). It is often argued that moth-

[3] In Spanish, "Chile Crece Contigo".

ers have stronger preferences for meeting the needs of children and therefore cash in the hands of mothers translates into better child outcomes (Blundell, Chiappori, & Meghir, 2005). By estimating a technology of skill formation within a collective setting, I am able to assess the extent to which targeting individual members in households actually translates into different child outcomes.

The dataset used in this article allows me to overcome some empirical limitations that the literature has faced previously. For instance, we know that parental skills largely determine children's skills (J. Heckman & Mosso, 2014). By having information on parental IQ tests and personality assessments, I am able to incorporate such facts into my estimation strategy. Additionally, we know that there is a multiplicity of skills that are relevant to determining adult life outcomes (Cunha et al., 2010). I incorporate multiple measures of skills across various dimensions, such as motor, communication, cognitive and behavioral abilities in children.

Moreover, we know that the productivity of time investments in children depends on the interactions between parents and children. Fiorini and Keane (2014) find that, when evaluating information about the time parents spend with children, it is important to differentiate among activities such as watching TV, educational activities with parents, and educational activities with other adults, as each of these translates differently into skill formation among children. By using data on the frequency with which parents perform fourteen different types of activities with their children, I am able to incorporate not only the time component but also the quality of interactions between parents and children. Additionally, I use geocoded datasets matching all the nationally registered childcare providers with the households in the survey in order to obtain information about the cost of investing in children. Households that have a relatively large supply of childcare services within their neighborhood might, in principle, find it easier to invest in their children through preschool services or monetary investments.

Finally, given that the survey used for this study was developed with the goal of precisely characterizing the skill formation process in children, I am able to provide a unique empirical description of parental investments in children. I observe the weekly frequency of consumption of different types of food for children, as well as availability of toys, books, and puzzles, as well as a precise characterization of which specific skills such elements might promote.

This paper also makes a methodological contribution to the estimation of dynamic microeconomic models with unobserved and continuous state variables. By implementing

an efficient simulation-based estimator using particle filtering techniques from the machine learning literature (Murphy, 2012), I show a feasible computational approach to dealing with the high dimensionality problem that arises in such models. Moreover, this is the first paper in the literature of household choices and child development that estimates a technology of skill formation through a dynamic latent-factor approach a-là Cunha et al. (2010). This allows me to obtain non-parametric identification of the skill production technology by using a large number of measures of skills for children. Furthermore, most of the research analyzing the skills formation process in children is carried out in the context of developed economies due to availability of data. By analyzing this process in the context of a developing country, I bring new insights regarding the skill formation process and the effect that policies and programs have on the skills of children in a situation where children face a large series of disadvantages.

This article proposes a new framework for estimating collective models of household behavior. There has been extensive study of the theoretical properties of the collective model of household behavior related to goods that are "public" within the context of the household (Blundell et al., 2005; Chiappori & Donni, 2009; Browning, Chiappori, & Weiss, 2014). However, there are still very few empirical studies (Cherchye, De Rock, & Vermeulen, 2012). The main challenge of estimating collective models of household behavior is that of identifying the bargaining power, or Pareto weight, of each household member. The common approach to deal with this issue is to observe the consumption of private goods within the household, such as gender-specific clothing, together with distribution factors. Distribution factors are variables that affect the final outcomes of households, by exclusively modifying the bargaining power of each member. Examples of distribution factors commonly used in the literature include local sex ratios, the proportion of non-labor income in the household that is in the hands of women, and the differences in ages between husband and wife. This approach assumes that the good observed is purely private (i.e., a husband does not care about his spouse's clothing) and also assumes that all the bargaining power is explained by the consumption of a single good. In this article, I use information from questionnaires related to female empowerment and gender roles, combined with information on distribution factors, in order to identify the bargaining power of each member of the household. By following such an identification strategy, I am able to allow for unobserved heterogeneity. In addition, the number of assumptions needed to identify the parameters of the model are less restrictive.

Among the main results, I find that there are significantly large gaps in skills between

rich and poor children at age 5. The gaps in skills between children in the lowest quintile of the income distribution and children in the highest quintile, are in between 0.3 and 0.7 standard deviations in tests measuring cognitive abilities, socio-emotional development, and vocabulary skills, among others. These inequalities are mostly explained due to differences in parental skills and monetary investments. Additionally, I find that fathers' time spent with children is 50% as productive as mothers' time and that mothers have stronger preferences for children. However, the higher productivity and the stronger preferences for children do not by themselves explain the observed disparities in time investments between mothers and fathers. The relative disempowerment of women explains around 15% of the difference: given that women are relatively less empowered than men, women tend to contribute a higher share in the production of public goods within the household.

The results of the estimates are used to simulate the effects that cash transfer programs, free childcare subsidies, and in-kind transfers have on the gap in skills between rich and poor children. Although less prevalent than the other two programs, in-kind transfers are currently being implemented in Chile through "Chile Grows with You". I find that in-kind transfers are much more effective than the other alternatives when it comes to closing the gaps in skills between rich and poor children.

The remainder of this article is structured as follows: In Section 2, I briefly review the literature in order to identify the main contributions of this article. I describe the data in Section 3. In Section 4, I present some preliminary evidence motivating the economic model, which will be described in Section 5. The estimation procedure, together with the relevant identification arguments, are introduced in Section 6. The main results of the paper are in Section 7. In Section 8, I discuss the main results from implementing various policies. I summarize the main points of this paper in Section 9.

2 Review of the literature

This article is related to four areas of the literature in economics. First of all, this paper is related to the literature analyzing how household behavior affects the production of skills in children. One of the most important decisions families need to make that will have consequences on the production of skills in children is that of labor supply. As household members increase the participation in the labor market this will bring more monetary resources to the household but the amount of time parents interact with their children is reduced. For this reason, it is not evident at first hand what is the impact of labor force

participation on the skills of children.

The question of how labor supply decisions affect the production of skills in young children has been somewhat explored in the literature. Bernal (2008) estimates a structural model of female labor force participation taking into account that skills are affected by family income and also by the total amount of time that mothers interact with their children. Due to limitations in the data, the author does not incorporate paternal time as a potential input in the skills of children. Taking into account the overall effect of an increase in income but a decrease in the amount of time that mothers interact with their children, the author finds that one year of full employment decreases the skills in children by approximately 0.13 standard deviations.

Del Boca et al. (2014) extend the results of Bernal (2008) in order to take into account both parents in the production of skills. The authors estimate a unitary dynamic model of household behavior where each parent allocates time to labor market, leisure, or to activities interacting with their children. Additionally, the authors incorporate the decision of how much money to allocate to monetary investments in their children or to consumption. The authors find that when mothers increase the amount of labor being supplied, the negative effect this might have is not only alleviated by the increase in the amount of resources brought from wages but also by the fact that the father starts to spend more time with the children at home. One of the main conclusions of the authors is that time of both, fathers and mothers, are relatively more important than monetary investments into the production of skills in children. Gayle et al. (2015) extends the modeling framework of Del Boca et al. (2014) in order to incorporate endogenous fertility in the household. However, they do not observe test scores in children or monetary investments from parents and ignore the role of preschool education.

The article that is most related to this paper is likely Del Boca et al. (2014). This paper improves upon Del Boca et al. (2014) in several points. First, I incorporate the decision of preschool services. This is important given that preschool services are one of the most important policies used from governments not only to improve the conditions in which children develop, but also with the goal of increasing female labor force participation.

Additionally, a major point in which this article departs from the analysis of Del Boca et al. (2014) is that I estimate a collective model of household behavior, allowing parents to have different preferences, as opposed to using the unitary approach. There are two reasons why this is an important contribution. First of all, cash transfers to families with children are given to their mothers. This, motivated by the fact that cash in the hands of

women seems to translate into better child outcomes than cash in the hands of men (Duflo, 2000; Attanasio & Lechene, 2014; Thomas, 1994). In order to assess the effect that targeting individual members have on child outcomes, and to identify the extent to which additional resources should be spent on targeting, I estimate a collective model of household behavior where parents have different preferences for children. Additionally, the empirical regularity that there is a positive correlation between women's empowerment and child development (Haddad, Hoddinott, Alderman, et al., 1997), cannot be explained by considering the household as a single entity with one utility function. This has motivated a large literature analyzing the relationship between female empowerment and child outcomes (Doepke & Tertilt, 2014). By rationalizing the behavior of the household through a collective approach, I am able to assess the extent to which empowering women can actually translate into better child outcomes.

Third, this is the first paper that estimates a model of parental investments and child outcomes by using observation not only on time investments but also on in-kind investments. The information used for this article includes a detailed description of the environment in which children grow. Enumerators who visited the households where trained in order to provide a precise characterization of how ideal an environment is for a child. For instance, not only I observe availability of toys, but I observe if the toys are ideal for the promotion of specific types of skills such as motor skills, behavioral skills or toys that help develop free expression in children. I observe availability of music for children, puzzles, books for children and costumes. Additionally, I have detailed information about the frequency with which children consume different types of food such as fruits, vegetables , fish, among others. This information is used in order to assess the effect of in-kind investments from parents in their children.

The dataset used in this project allows me to incorporate several facts about the skill formation process in children that was not incorporated in Del Boca et al. (2014). First of all, there is a consensus in the literature stating that skills are multiple (emotional, physical, cognitive) and that they interact with each other in the process of skill formation. In this article, rather than using one cognitive test score as a measure of skills, I use various indicators of motor development, cognitive achievement and emotional attainment in young children as broad measures of skills in children. Additionally, an important element in the process of skills formation in children is their dependence on parental skills (Francesconi & Heckman, 2016). Ignoring parental skills when estimating a production function of skills in young children might bias the effect of other inputs, such as time or

in-kind investments. I overcome this limitation by using various assessments of cognitive achievement and personality traits of parents in the estimation exercise.

My estimation strategy also improves upon Del Boca et al. (2014). By implementing a dynamic latent factor structure in the estimation of the skill production function for children, I am able to obtain non-parametric identification of the skill production function in children. This is accomplished by using identification results from the literature of skill formation in children Cunha et al. (2010), combined with the large amount of information available in the dataset. Because of that, the results of the estimation are less sensitive to the specific parametric form assumed for the skill formation technology, and the bias arising from measurement error is reduced, making the results more robust. This, along with the fact that a latent factor structure can be interpreted as unobserved heterogeneity (Carneiro, Hansen, & Heckman, 2003), and potentially improves the accuracy of the estimates, has made factor analysis a popular tool to get accurate estimates of the production function of skills (Cunha et al., 2010; Cunha & Heckman, 2008; J. J. Heckman, Stixrud, & Urzua, 2006). This article is the first to estimate production function of skills via a latent-factor approach, nested within a collective model of household behavior.

The second area of the literature to which this article is related is to the empirical implementation of collective models of household behavior. The income pooling assumption establishes that in a household composed by various members, it does not make a difference if transfers are being done to one member or the other. Ultimately, what matters, is the overall resources of the household. Such assumption has been rejected in contexts as diverse as Sweden (Cesarini, Lindqvist, Notowidigdo, & Ostling, 2013), South Africa (Duflo, 2000), Mexico (Attanasio & Lechene, 2014) Brazil, the US and Ghana (Thomas, 1994). This has motivated a significant amount of research towards exploring different alternatives. The collective model of household behavior assumes that each parent has his-her own preferences and the decision reached in the household is Pareto efficient (Chiappori & Donni, 2009). Such alternative has proved to have better empirical predictions than the unitary framework.

Although there is extensive literature exploring the properties of the collective model of household behavior, there are still very few empirical implementations of such model, one exception being Cherchye et al. (2012). In their model, the authors assume that each parent has his or her own preferences and each parent derives utility from the time they spend with their children. By following such an approach, they ignore the fact that the amount of time parents spend on their children might have an impact on their skills. This

present article contributes to the literature related to the collective model of the household by being the first one to rationalize such model of household behavior taking into account the production of skills in children.

Additionally, this article provides a new framework for identifying collective models of household behavior. The usual identification strategy of such models relies on observing the consumption of a given number of private goods, clothing being the most popular choice. Once the decisions of consumption of such private goods are observed, there is a one-to-one mapping from these decisions into the Pareto weight given to each agent. However, such arguments deny the fact that every good consumed within the household has a public component, as it is reasonable to assume that couples care about each other's clothing, for example. In this article I use a novel estimation strategy for collective models of household behavior. Rather than using private goods, I use answers provided from questionnaires of female empowerment and gender roles as noisy measures of the bargaining power within the household.

This article also contributes to the literature that addresses how to design optimal policies to disadvantaged households in developing countries. Currently, Conditional Cash Transfers (CCT) are one of the most important policies to alleviate poverty and reduce inequality in most developing countries. Every country in Latin America has a CCT program and in some cases, such as in Brazil and Mexico, this single program accounts for the largest social assistance program executed by the central government (Fiszbein et al., 2009). In most countries, the design of such program establishes that in households with children, the mother of the child should be the person receiving the monetary transfers. This is supported by findings such as in Bobonis (2009) and Duflo (2000) where the authors explore whether or not the gender of the recipient of a monetary transfer matters in terms of child development. In both cases it is found that transfers made to women translate into better child outcomes than those made to men. The common interpretation of this fact is that preferences of women are more aligned with that of child outcomes and making the transfers to them is more efficient. However, in order to establish what mechanism is generating such outcome it is necessary to estimate an economic model able to identify all possible channels.

The finding that transfers made to women translate into better child outcomes still deserves some analysis from the literature. Although one valid interpretation is that women are expected to spend their own income on public goods within the household, as explained by Bobonis (2009), or to the fact that they simply have stronger preferences for child

outcomes than men, there are multiple possible explanations. Blundell et al. (2005) show that as long as the marginal willingness to pay for child outcomes is higher for women than for men we will have such a result. However, having women with stronger preferences for child outcomes is not a necessary condition for such statement. Similarly, Basu (2006) provides an example where even in the case in which women care more for their children, there might be an inverted-U relationship between the bargaining power of the women and the welfare of children as once women become relatively more powerful they can devote all the resources derived from child labor into their own private consumption. All this shows that it is important for the design of policies to understand which is the mechanism generating the positive relationship between women empowerment and child outcomes. In this article I explicitly allow parents to have different preferences for children and by estimating the structural parameters of the model I can analyze which mechanisms generate such relationship.

Finally, this article is related to the literature exploring the production of skills in children. Todd and Wolpin (2007) present different alternatives to estimating the production function of cognitive skills in children depending on the type of data available to the researcher. Cunha et al. (2010) estimate a production function of skills in children taking into account that the productivity of inputs might vary with age. As both inputs and outputs are observed with error the authors estimate such production function via a dynamic latent factor structure. In this article I use the estimation methods presented in Todd and Wolpin (2007) taking into account that the availability of data allows me to use a value-added specification and for the econometric implementation I will use a latent factor structure as in Cunha et al. (2010). However, in order to solve for the endogeneity of inputs I will use the economic model of household behavior. Although Cunha et al. (2010) is considered as a seminal contribution to the literature of production of skills, there is little scope for counterfactual analysis as the inputs are hard to interpret: the measures of investments into the production function do not map to any possible effort level or monetary investment in the family. In this article, by linking the literature of household behavior and skills production within a latent factor framework, counterfactual analysis can be performed with easy interpretation of findings.

Additionally, this is one of the few articles that have attempted to estimate a production function of skills in a developing country. Much attention has been focused on the United States and Europe due to the availability of data. For the purpose of this article I will use a unique dataset from Chile that will bring the estimation of production of skills

into a new context. A final contribution of this paper relies on the estimation strategy. Estimating dynamic models with continuous state variables is a huge challenge in microeconomics. Different solutions such as discretization (Keane, Todd, & Wolpin, 2011) have been proposed. I bring to the table a new alternative commonly used in macroeconomics and macro econometrics: particle filtering techniques.

3 Data and Preliminary Evidence

I will use a rich longitudinal dataset from Chile. Chile is the country of Latin America with the highest GDP per capita -$US 20,000 PPP- and is often considered a case of economic success in the region due to the good economic performance during the last twenty years[4]. Two of the most distinctive facts about Chilean economy are it's high level of inequality and the low levels of female labor force participation. Women's participation in the labor market has been historically low not only when the comparison is made with developed economies but also with similar countries in terms of income and geographic location.

The dataset used for this project comes from the Early Childhood Longitudinal Survey from Chile (ECLS). The first wave of this survey was collected in 2010 and includes a nationally representative sample of all households in Chile with a child under 5 years of age, which accounts for 15,175 households. The second wave was implemented in 2012 and included 85% of the households in the original sample and a new sample of 3,135 new households with children younger than 2 years of age. In each wave information about labor force participation for every member older than 15 was collected, together with income, educational background, knowledge about the process of early childhood development and productive routines performed with the child such as reading books, teaching letters and taking children to the park.

The dataset includes multiple test scores solved by the children and questionnaires answered by the primary caregiver of the child in order to assess the skills level of children, for different domains such as socio-emotional development, behavioral problems and development of vocabulary. Unfortunately, not every test was answered by all the children as all of them include different age specifications[5]. The description of the tests included

[4]Chile is considered since 2012 as a developed country for the World Bank. However, most of the literature treats it as a developing country, specially when dealing with data pre 2012. The International Monetary Fund does not include Chile in the list of advanced economies.

[5]For instance, the Batelle Index of Development, a questionnaire included in the 2010 survey to be answered by the primary caregiver of the child, is designed for children between 6 and 24 months of age. Given that

in the sample is included in Tables 1 and 2. These test scores will be considered a noisy signal of the true level of skills for children.

Given that I want to identify how families make decisions of investments in young children, I restrict the sample to children living with both biological parents. I do this because the main goal of the article is to be able to identify how parents reach such decisions in a context where there are multiple members with plausibly different preferences.

In the economic model I will consider the case of families with only one child under the age of five. For that reason, I will take into account families with only one child or with multiple ones so long as the child being analyzed has no siblings within a five years age range[6]. The reason for doing this is that allowing for multiple children in the economic model would imply solving additional questions that are not the main goal of this article. For instance, we would need to identify or take a stance on whether parents have the same preferences for boys and girls, or if they have preferences for equality of skills among children or rather they would devote more resources to the most promising child. Moreover, we also would need to understand to what extent there is a quality-quantity tradeoff in the fertility decisions: do parents prefer to have more children and devote fewer resources to each of them or terminate early their fertility and devote most resources to a limited number of children.

The sample used for the estimation of the model includes only families with children, in which both parents live together and where the child has no siblings within a five years age range. Moreover, given that I use test scores and measures of health at birth in order to estimate the production of skills, I drop from the sample families that did not complete such questionnaires. The description of how the sample is selected is described in Table 3. The sample considered for the analysis consists of 950 families. Some descriptive statistics of the sample used, for the 2012 wave, are included in Table 4 and some details about the age distribution of the children included, for the 2012 wave, are included in Table 5.

We see that fathers, whose average age is 37, are on average three years older than mothers, whose average age is 34. There is not much difference in terms of schooling as both fathers and mothers attain on average 11 grades of education. We do observe significant differences between fathers and mothers in labor market variables. Fathers participate in the labor force on average 43 hours a week, which is almost twice the average of mothers,

most children are older than 24 months in the 2010 survey, I do not include this test when performing the analysis of skills in young children.

[6] A similar data restriction is implemented in Bernal (2008)

at 24 hours. As will be mentioned in the preliminary evidence section, unemployment does not explain a great deal of the low levels of hours that mothers participate in the labor market. It is rather due to women being actively out of the labor force, not looking for a job but rather reporting that they don't work because they have to take care of their children.

There are differences in the wages of men and women on a weekly basis. The weekly wage of a woman is $82,730 Chilean Pesos (CLP) whereas men make $85,480[7]. In terms of ages of children, we see that the sample includes a somewhat homogeneous group as the average age is five years old, the oldest one being six and the youngest one being four.

The survey also reports the frequency with which parents perform different types of activities with their children. The description of each of these activities is presented in Tables 6 and 7. In Figure 1 I present the average frequency for each activity that parents report performing with the child for the activities reported in 2012. As can be seen, in every activity fathers report a lower frequency than mothers. The most common activities that parents perform with their children is sharing a meal, talking to them and teaching them the numbers or letters. The least common activities are taking the children to cultural activities, parks or reading to them.

A novel feature of this dataset is the inclusion of questions regarding female empowerment and gender roles within the household. For instance, there is information on whether it is the mother or the father who administers the income and whether the mother considers that it is better to have a bad marriage than to remain single. These variables allow us to identify to what extent the woman has a saying in the household and if she has some power at all when making the decisions of economic relevance. The variables used to assess the degree of women empowerment in the household are presented in Table 14. Tables 15 and 16 include summary statistics of the answers provided about the empowerment questionnaires. It is interesting to see, for instance, that 64% of men think that women should devote all their time to taking care of children and should work only in the case there is remaining time. However, as noted in Table 16 women also consider that they should be more in charge of children than working, as for instance the question related to "A woman in charge of chores should not work" receives an average score of 2.62 out of 4. These facts show that female empowerment should be an important concern for policymakers in this subpopulation.

[7]The exchange rate for 2012 corresponds to $1 Chilean peso for $0.002 USD

The dataset also contains information about other important inputs into the production of skills in children. For instance, there is significant information about issues for the child during pregnancy and the health conditions at birth. This information will be used in order to assess the skills of children at birth. The indicators of health at birth and conditions during pregnancy are reported in Table 10.

A relevant input into the production of skills is the amount of monetary investments that parents make in their children. These type of investments can be considered as any type of materials that can improve the living conditions of children or that can stimulate the learning experiences of children such as toys, food investments, physical space exclusively used by the child, and so on. Previous studies such as Del Boca et al. (2014) and Bernal (2008) take into account such factors into the production of skills in children but do not observe such measures of investments. The identification of how monetary investments affect the production of skills in children in their studies relies then on functional forms assumption. Contrary to previous cases in the literature, I will use some indicators of parental investments in children that will give some idea of how parents invest in their children. Some of these measures are exactly the same as used in Cunha et al. (2010), which come from the HOME inventory test score. The details of the measures used to asses the level of monetary investment in the children can be found in Tables 13 and 12.

4 Preliminary Evidence

In this section I will present four facts found in the dataset that motivate the economic model developed in the next section.

4.1 Gaps in skills emerge early in life

When analyzing height at birth, weight at birth and the incidence of pre-term births[8], for different income groups, we do not observe huge differences between poor and rich children, as can be seen in Figure 2. However, we do observe differences in various dimensions of development such as vocabulary, communication skills, motor skills and cognitive achievement, when children are five years olds. This can be seen in Figure 3. The figure reports the standard deviations below-above the mean for each income group. We see, for instance, that children in the lowest income quintile score 0.1 standard deviations below

[8]These are variables that have often be used as a measure of health at birth (Sørensen et al., 1999).

the mean in the Battelle test score for Motor Skills whereas children in the richest quintile score 0.15 standard deviations above the mean. The most dramatic case is vocabulary, where children in the lowest income quintile score 50% of a standard deviation below children located in the richest income quintile. This early emergence of gaps in the development of children is consistent with the literature (Schady et al., 2015; Cunha et al., 2010).

4.2 Low levels of female participation in the labor market are not explained by female unemployment

As mentioned before, mothers participate on average 24 hours a week in the labor market whereas fathers do so 43 hours a week. One plausible explanation can be due to unemployment: it is harder for women to find a job and because of that they do not actively participate in the labor market. However, it turns out to be the case that female unemployment in the population analyzed is low, below 5%. The main reason for observing these low levels of female participation in the labor market is due to voluntary unemployment: women decide not to participate in the labor market. As can be seen in Figure **??**, this is characteristic of women across all age groups. Most of them are not working or looking for a job and 83% of them argue that the main reason they do not do it is because they are taking care of children.

The fact that unemployment plays a small role in explaining the low levels of female activity in the labor market should guide the economic model as to how to approach the problem of deciding whether or not to work. Including frictions in the model, as is usually done in the literature in order to explain unemployment and variation in earnings for observationally equivalent agents, would complicate the model and the gains from doing so might not be significant. Because of this, I will simplify the usual decision of labor force participation as is usually done in the neoclassical model of household behavior, where people decide whether or not to work at a given wage recognized by the market.

4.3 Mothers spend more time with children than fathers

As shown previously in Figure 1, mothers spend more time with their children, in every activity, than fathers do. One possible explanation for this factor is given by the labor supply differences. Fathers specialize in remunerated activities in the labor market whereas mothers do so taking care of children. In Tables 17 and 18, I analyze the relationship be-

tween labor supply and time spent with the child of both spouses. In order to simplify the analysis, I construct a measure of time investment via principal component analysis and I regress the predicted factor with other covariates of the family. We observe that there is a negative correlation between time spent with the child and labor supply decisions for both fathers and mothers, in the two waves of the dataset being used, as can be seen in Tables 17 and 18.

Additionally, we observe a positive correlation between each parent's own effort and the labor supply of his/her spouse. This might be evidence of compensating behavior arising from parents as when one parent increases his/her labor supply, that parent decreases the amount of time spent with their children and thus the other parent might react by increasing the amount of time interacting with their child. This compensating behavior might diminish the plausible negative impact on child development of an increase in female labor force participation.

Although labor market behavior might explain part of the differences in the time investments between mothers and fathers, there are other stories consistent with such result. The differences might be due to preferences, as mothers find it less costly to invest time with their children, or due to productivities, as the amount of time that mothers spend with their children might be more efficient in enhancing children's skills than that of fathers. Moreover, there is a possible explanation related to the fact that the utility derived from children's skills is a public good but the time investments are privately exerted. As women are relatively less empowered than men, the cost of effort exerted by women is less than the cost of effort exerted by men. This implies that even with the same preferences and resources, women would spend more time taking care of children. In the economic model I allow all these aforementioned factors to be a possible explanation of the differences in time investment between fathers and mothers.

4.4 There is a positive relationship between female empowerment and child outcomes

The last point to be mentioned in the preliminary evidence section is the correlation between female empowerment and child outcomes. There is evidence in the literature pointing at the fact that women empowerment is associated with better child outcomes in various contexts (Attanasio & Lechene, 2014; Thomas, Contreras, & Frankenberg, 2002).

We do observe evidence of a positive relationship between female empowerment and

child outcomes. Tables 19 and 20 present the results of various regressions showing positive correlations between child outcomes and the share of income earned by women. Even after controlling for variables such as IQ level of primary caregiver, total household income, grades of schooling of both parents and their ages, we do observe a positive relationship between the share of the total household income earned by mothers and children's outcomes.

When analyzing the responses to the female empowerment questionnaires, we also observe a positive relationship between female empowerment and investments in children. In Table 21 some regressions of child investments and female empowerment are presented. We show again, that even after controlling for the same variables as mentioned before, those households where women are relatively less empowered make fewer investments in their children. Those households where the woman administer the income are more likely to have toys for the development for children, and the frequency of consumption of fruits and vegetables and cookies and candies is higher whereas that of bread is smaller. Similarly, those households where the opinion that women should not work and take care exclusively of children is more accepted, are more likely to see their children sharing their bed with somebody else.

The results of these regressions cannot be interpreted as incorruptible evidence of a causal relationship between female empowerment and child outcomes. Nonetheless, they suggest that there is either some unobservables that are not captured in the regressions, that are also correlated with female empowerment, and that affect positively child outcomes, or that it is indeed female empowerment that improves the conditions of children in the households. In order to incorporate such findings in the economic model, I allow parents to have different preferences regarding leisure, consumption, skills in children, among others, so that we can understand the relationship between female empowerment and child outcomes arising from such patterns or either due to unobserved heterogeneity.

5 Economic Model

In this section I describe the economic model used to rationalize investments in children altogether with household behavior. Each household (h) is composed of two agents (j); namely the father (f) and the mother (m). In each household there is also a child with a

level of skills denoted by (s) who is not a decision maker[9]. In each period t, parents make decisions of time investments in their children (e_t^j) and monetary investments for the child (I_t), private consumption (c_t^j) and labor market (h_t^j) decisions. I assume that the decision of labor market participation is only done at the extensive margin, that is, members decide whether or not to participate in the labor market: $h_t^j \in \{0,1\}$. Additionally, during the first period parents need to decide if the child attends preschool services or not (a_t) and then a_t can take the values of zero or one depending on whether the child goes to preschool or not.

There is a preference shock $\boldsymbol{\epsilon_t}$ associated with each decision of labor supply and preschool service. As there are two decisions of labor supply and two possible of preschool services this shock is four-dimensional. In particular, the choice set for labor supply and childcare decisions is given by $D_t = \{(h_t, a_t) : h_t \in \{0,1\}, a_t \in \{0,1\}\}$. $q_t^{j,d}$ is an indicator function for individual j in period t taking the value of 1 if decision $d \in D_t$ is taken and 0 otherwise. I assume the preference shock follows a multivariate normal distribution with mean zero and variance Ω. The flow utility derived for each parent j in time t is given by the following utility function:

$$u_t^j(c_t^j, h_t^j, e_t^j, d_t^j, s_t) = \alpha_{1,t}^j \ln(c_t^j) + \alpha_{2,t}^j \ln(s_t) - \alpha_{3,t}^j(h_t^j) - (1 + h_t^j)\alpha_{4,t}^j e_t^j - \alpha_{5,t}^j h_t^j(1 - a_t) + \epsilon_{d,t}^j q_t^{j,d} \quad (1)$$

where $\epsilon_{d,t}^j$ is the d-th element of the vector $\boldsymbol{\epsilon_t}$. Additionally, I allow the cost of time investments in children $\alpha_{4,t}^j$ to change if there is an additional person helping with household chores such as cleaning the house, cooking or taking care of the child. Specifically, I set $\alpha_{4,t}^j = \alpha_{4,0,t}^j + \alpha_{4,1,t}^j HM_t$, where HM_t takes the value of one if there is a person helping with the household chores, and zero otherwise.

At period t the skills of the child depend on monetary investments (I_t), time investments from both parents (e_t^j), preschool attendance (a_t), the skills of the mother of the child (PG) that is constant over time[10], the previous level of skills (s_{t-1}) and the age of the child in months (τ_t). I allow for unobserved heterogeneity in the production of skills denoted by

[9] This is a common assumption in the literature (Del Boca et al., 2014; Bernal, 2008) that seems reasonable given the little influence that children under six years of age can have on the resources allocation of the household.

[10] There is evidence pointing to the fact that cognitive skills remain stable at around age 8 and non-cognitive skills are stable during adult life (Borghans, Duckworth, Heckman, & Ter Weel, 2008; Roberts, Kuncel, Shiner, Caspi, & Goldberg, 2007). For this reason, assuming that skills of the mother are stable are not unreasonable.

$(\eta_{s,t})$. The distribution of the unobserved heterogeneity term $f_{\eta_{s,t}}$ is gender specific. The variable Members_t denotes the number of household members present in period t in the household. The idea is to capture that by having additional household members not only the production of skills might be affected but also the productivity of each input. The production of skills is specified in the following equation:

$$s_t = r_t s_{t-1}^{\theta_0} \tilde{I}_t^{\theta_1} e_t^{\theta_2} \tag{2}$$

where r_t denotes the total factor productivity specified as:

$$r_t = \underbrace{\exp\left(\delta_0 + \delta_1 \tau_t + \delta_2 a_t + \delta_{3,t} PG + \delta_4 \text{Members}_t + \eta_{s_t}\right)}_{\text{Total Factor Productivity}} \tag{3}$$

e_t is the total time effort invested in the child given by the production function:

$$e_t = \underbrace{\left[\gamma_0 \left(\tilde{e}_t^f\right)^{\phi} + \gamma_1 \left(\tilde{e}_t^m\right)^{\phi}\right]^{1/\phi}}_{\text{Total time investment}} \tag{4}$$

where

$$\tilde{e}_t^j = e_t^j \exp\left(\eta_{e_t^j}\right) \tag{5}$$

and

$$\tilde{I}_t = I_t \exp\left(\eta_{I_t}\right) \tag{6}$$

The terms $\eta_{e_t^j}$ and η_{I_t} are unobserved heterogeneity. This term captures the fact that parents can differ in how productive they are in terms of the time effort and monetary investments in their children in unobserved ways. That is, even with the same amount of effort and monetary investment, the productivity of these inputs might be different across households. The terms $\eta_{I_t}, \eta_{e_t^j}$ and $\eta_{s_t^j}$ are complete information in the sense that parents make decisions knowing the productivity of their own inputs at every point in time.

5.1 Dynamic problem

I assume that parents need to make investment decisions for two periods. Each period lasts for two years and the first period starts when children are on average three years old. After the two periods, children enter a different stage in which parents and children face a different set of incentives in the process of skills production. Parents face a different set of incentives given that children start the formal schooling years and children start behaving more as an agent making their own decisions that might have consequences in their own skills. For this reason, I only model childhood lasting for two periods: birth to age 3 and age 3 to age 5. This assumption is commonly made in the Literature. Bernal (2008) assumes that early childhood relevant decisions are made until age 5. Del Boca et al. (2014) model household behavior until children are 16 years old but only use information on two periods to estimate their model, that is when children are on average four and nine years old, respectively.

$$V_2(\Psi_2) = \max_{\{I_2, \{c_2^j, e_2^j, c_2^j, h_2^j\}_{j=m,f}\}} \mu_2 u_2^f(c_2^f, h_2^f, e_2^f, d_2^f, s_2) + (1-\mu_2) u_2^m(c_2^m, h_2^m, e_2^m, d_2^m, s_2) \quad (7)$$

Ψ_2, which will be defined below, includes the state variables relevant to the decisions made in the second period, $\mu \in [\underline{\mu}, \bar{\mu}] \subseteq [0,1]$ represents the Pareto weight or bargaining power of the father. The solution for the problem of the household should satisfy the technological constraint given in 2, the time constraint for each agent:

$$h_2^j \in \{0,1\}, \text{ for } j = m, f \quad (8)$$

the non-negativity constraint:

$$c_2^f, c_2^m, I_2, e_2^f, e_2^m \geq 0 \quad (9)$$

and the budget constraint

$$c_2^f + c_2^m + P_{I,2} I_2 = Y_2^f + Y_2^m + w_2^m h_2^f + w_2^f h_2^f + \Xi_2 \quad (10)$$

where w_2^j represents the wage offer for individual j, Y^j is the corresponding non-labor income, and Ξ_2 is the total non-labor income that cannot be attributed to any specific

household member[11]. $P_{I,2}$ is the price of monetary investments in children for the second period. Note that in the second period parents don't make decisions regarding childcare attendance as virtually every child in the sample goes to preschool during the second period.

The problem of the household during the first period is given by:

$$V_1(\Psi_1) = \max_{\{I_1,\{c_1^j,e_1^j,c_1^j,h_1^j\}_{j=m,f}\}} \mu_1 u_1^f(c_1^f, h_1^f, e_1^f, d_1^f, s_1) + (1-\mu_1)u_1^m(c_1^m, h_1^m, e_1^m, d_1^m, s_1) + \beta V_2(\Psi_2) \tag{11}$$

subject to the skill production technology given in 2, the budget constraint:

$$c_1^f + c_1^m + P_{I,1}I_1 + P_a a = Y_1^f + Y_1^m + w_1^m h_1^f + w_1^f h_1^f + \Xi_1 \tag{12}$$

where P_a is the price of taking the child to preschool services and a can take the value of zero or one depending on whether or not the child goes to preschool services.

I assume that wages follow a Mincer equation:

$$\ln(w_t^j) = \beta_0^j + \beta_1^j yrschool_t^j + \beta_2^j age_t^j + \beta_3^j (age_t^j)^2 + \varepsilon_{t,w^j} \tag{13}$$

where $\varepsilon_{t,w^j} \sim N(0, \varepsilon_{w_j})$ is measurement error[12]. Additionally, the relative importance of each household member will depend on characteristics of the household. In particular, I assume the following parametrization of μ_t:

$$\mu_t(E_t) = \frac{\exp(\Lambda' E_t + \eta_{\mu_t})}{1 + \exp(\Lambda' E_t + \eta_{\mu_t})} \tag{14}$$

where $\Lambda \in \mathbb{R}^L$ is a vector of coefficients; X are variables affecting the the relative bargaining power of each member in the household and $\eta_{\mu,t}$ is unobserved heterogeneity. $\underline{\mu}$ and $\bar{\mu}$

[11] Examples of elements included in the Ξ_2 term are subsidies for water consumption for the household.

[12] Note that I am imposing a separate distribution for men and women. We could assume that all the correlation is yet given by assortative mating and is no necessity to assume a bivariate distribution in their wages. The only difference will be to estimate an additional parameter which will be the correlation between wage offers

are the lower and upper bounds for the Pareto weight [13]. In the E_t variables I include the ratio of offered wages, the difference of ages between spouses, the difference in grades of schooling and the father's share in non labor income. Additionally, I include conditions of the local labor market that include the relationship between male and female unemployment, the sex ratio and the wage ratio in the region of residence of the household. Similar specifications to this one have been used previously in the literature [14].

$$E_t = \left[\frac{w_t^f}{w_t^m}, \frac{Y_t^f}{Y_t^f + Y_t^m}, age_t^f - age_t^m, yrschool_t^f - yrschool_t^m, \frac{\bar{Female}_t}{\bar{Male}_t}, \frac{U^{Male_t}}{U^{Female_t}}, \frac{w^{Male_t}}{w^{Female_t}} \right] \tag{15}$$

where $\bar{U}$ denotes the unemployment rate for each gender $\frac{\bar{Female}_t}{\bar{Male}_t}$ is the sex ratio in the region of residence of the household, and $\frac{w^{Male_t}}{w^{Female_t}}$ is the wage ratio between women and men in the region of residence. These variables are what the literature refers to as distribution factors, variables that affect the behavior of the household only through its direct impact on the bargaining power. Descriptive statistics of these variables can be found in Table 22. The price of investments and the price of childcare depend on the availability of preschool services in the neighborhood through the following specification:

$$P_a = \text{Pchildcare}_{a,0} + \text{Pchildcare}_{a,1} DChildcare \tag{16}$$

$$P_I = \text{Price}_{I,0} - \text{Price}_{I,1} Dens \tag{17}$$

where $DChildcare$ is the distance to the nearest preschool provider and $Dens$ is the number of preschool providers within 5km from the household.

The state variables are given by:

$$\Psi_t = \{r_t, s_{t-1}, \boldsymbol{\eta}, \boldsymbol{\epsilon_t}, \Xi_t, E_t, \{\epsilon_{d,t}^j, Y_t^j, w_t^j\}_{j=m,f}, P_a, P_I\} \tag{18}$$

where the vector $\boldsymbol{\eta}_t$ collects the unobserved heterogeneity:

$$\boldsymbol{\eta}_t = \{\eta_{I_t}, \eta_{e_t^f}, \eta_{e_t^m}, \eta_{\mu_t}, \eta_{s_t}\} \tag{19}$$

[13] The assumption that μ is bounded given by $\mu \in [\underline{\mu}, \bar{\mu}] \subseteq [0,1]$ is made without loss of generality.

[14] Again, this determinant of bargaining power has been previously used in the literature (Cherchye et al., 2012), Bruins (2015) and Browning, Chiappori, and Lewbel (2013)

I assume that household members have perfect information regarding the terms related to unobserved variables at all moments. That is, in the first period they know the levels of their preference shocks and unobserved heterogeneity in the second period.

5.2 Model solution

Note that the model involves a set of discrete choices -childcare and labor supply- together with continuous decisions such as investment, effort and consumption. The way I solve this is to first find the optimal decisions of investment, consumption and effort, for each labor supply-childcare decision, and then chose the discrete alternatives that derives the highest utility. Given the dynamic nature of the problem, I first solve for the second-period problem. The solution is given by:

$$e_2^{m,*} = \frac{\kappa_2^2(\mu_2)\theta_2\gamma_1}{(1-\mu)\alpha_{4,2}^m(1+h_2^m)}\xi_2(m)\exp\left(-\eta_{e_2^m}\right) \tag{20}$$

$$e_2^{f,*} = \frac{\kappa_2^2(\mu_2)\theta_2\gamma_0}{\mu\alpha_{4,2}^f(1+h_2^f)}\xi_2(f)\exp\left(-\eta_{e_2^f}\right) \tag{21}$$

$$I_2^* = \frac{\kappa_2^2(\mu_2)\theta_1\left(h_2^f w_2^f + h_2^m w_2^m + Y_2^f + Y_2^m + \Xi\right)}{\kappa_2^1(\mu_2) + \kappa_2^2(\mu_2)\theta_1 P_I}\exp\left(-\eta_{I_2}\right) \tag{22}$$

$$c_2^{f,*} = \max\{\frac{\alpha_{1,2}^f\mu_2 I_2}{\theta_1\kappa_2^2(\mu)}, \zeta\} \tag{23}$$

$$\tag{24}$$

$$c_2^{m,*} = \max\{\frac{\alpha_{1,2}^f \mu_2 I_2}{\theta_1 \kappa_2^2(\mu)}, \zeta\} \tag{25}$$

$$e_1^{m,*} = \frac{\left[\kappa_2^2(\mu_2)\theta_2 + \beta\kappa_2^2(\mu_2)\theta_2\theta_0\right]\gamma_1}{(1-\mu)\alpha_{4,2}^m(1+h_2^m)}\xi_1(m)\exp\left(-\eta_{e_1^m}\right) \tag{26}$$

$$e_1^{f,*} = \frac{\left[\kappa_1^2(\mu_1)\theta_2 + \beta\kappa_2^2(\mu_2)\theta_2\theta_0\right]\gamma_0}{\mu\alpha_{4,2}^f(1+h_2^f)}\xi_1(f)\exp\left(-\eta_{e_1^f}\right) \tag{27}$$

$$I_1^* = \frac{\left[\kappa_1^2(\mu_1)\theta_1 + \kappa_2^2(\mu_2)\theta_0\theta_1\beta\right]\left(h_2^f w_2^f + h_2^m w_2^m + Y_2^f + Y_2^m + \Xi - P_a a\right)}{\kappa_1^1(\mu_1) + \kappa_1^2(\mu_1)\theta_1 + \beta\theta_0\theta_1\kappa_2^1(\mu_2)}\exp\left(-\eta_{I_1}\right) \tag{28}$$

$$c_1^{f,*} = \max\{\frac{\alpha_{1,2}^f \mu_2 I_2}{\theta_1\kappa_1^2(\mu_1) + \beta\theta_0\theta_1\kappa_2^2(\mu_2)}, \zeta\} \tag{29}$$

$$c_1^{m,*} = \max\{\frac{\alpha_{1,2}^f \mu_2 I_2}{\theta_1\kappa_1^2(\mu_1) + \beta\theta_0\theta_1\kappa_2^2(\mu_2)}, \zeta\} \tag{30}$$

where

$$\xi_t(j) = \frac{\left(\gamma_j \mu \alpha_{4,t}^f(1+h_t^f)\right)^{\frac{\phi}{1-\phi}}}{\gamma_0\left[\gamma_0(1-\mu)\alpha_{4,t}^m(1+h_t^m)\right]^{\frac{\phi}{1-\phi}} + \gamma_1\left[\gamma_1\mu\alpha_{4,t}^f(1+h_t^f)\right]^{\frac{\phi}{1-\phi}}} \tag{31}$$

$$\kappa_t^i(\mu) = \mu\alpha_{i,t}^f + (1-\mu)\alpha_{i,t}^m \tag{32}$$

$$\zeta = 1.0e-5 \tag{33}$$

and

$$\gamma_j = \begin{cases} \gamma_0 \text{ if } j = f \\ \gamma_1 \text{ if } j = m \end{cases} \tag{34}$$

The optimal decisions of labor supply and childcare are given by:

$$(h_2^{f,*}, h_2^{m,*}) = \max_{\{h_2^f, h_2^m\}} \mu_2 u_2^f(c_2^{f,*}(h_2^f, h_2^m), h_2^f, e_2^{f,*}(h_2^f, h_2^m), d_2^f(h_2^f, h_2^m), s_2(h_2^f, h_2^m)) +$$

$$(1-\mu_2) u_2^m(c_2^m(h_2^f, h_2^m), h_2^m(h_2^f, h_2^m), e_2^{m,*}(h_2^f, h_2^m), d_2^m(h_2^f, h_2^m), s_2(h_2^f, h_2^m)) \tag{35}$$

$$(h_1^{f,*}, h_1^{m,*}, a) = \max_{\{h_1^f, h_1^m, a\}} \mu_1 u_1^f(c_1^{f,*}(h_1^f, h_1^m, a), h_1^f, e_1^{f,*}(h_1^f, h_1^m, a)), d_1^f(h_1^f, h_1^m, a), s_1(h_1^f, h_1^m, a)) +$$

$$(1-\mu_1) u_1^m c_1^m(h_1^f, h_1^m, a), h_1^m(h_1^f, h_1^m, a), e_1^{m,*}(h_1^f, h_1^m, a), d_1^m(h_1^f, h_1^m, a), s_1(h_1^f, h_1^m, a))$$

$$+ \beta \left[V_2(\Psi_2(h_1^f, h_1^m, a) \right] \tag{36}$$

6 Estimation

The main challenge in the estimation of this model is that we do not observe the main features of the model in the dataset. Rather, we observe measures about the relevant factors of the model that are contaminated by measurement error. Specifically, I define the set K to include the latent variables in the model:

$$K = \{\{\ln(s_t), \ln(e_t^{f,*}), \ln(e_t^{m,*}), \ln(I_t^*), \mu\}_{t=1,2}, \ln(PG), \ln(s_0)\} \tag{37}$$

Rather than observing them directly, we have a set of measures that give some information about the true latent level of each variable. Such relationships between the measures and the latent factors can be described in the following system:

$$Z_m^k = \iota_{m,0}^k + \iota_{m,1}^k k + \varepsilon_m^k \text{ for } m = 1...N_k \tag{38}$$

where Z_m^k denotes the measure m for the latent variable k and N_k denotes the number of measures available for the latent factor k. The variables used as measurements for each factor are described in Tables 6 - 13. I assume the ε_m^k are uncorrelated across observations and follow a distribution $\mathcal{N}(0, \sigma_{km})$. However, as will be shown later, this assumption is not necessary for identification.

Given the structure of the model, there is a well-defined likelihood function denoted by:

$$P(O|X;\Theta) = \mathcal{L}\left(\Theta|O;X\right) \tag{39}$$

where (O) denotes the observed outcomes in the three periods: $O = \{O_0, O_1, O_2\}$ and X is the set of exogenous characteristics in the model. The set of outcomes for the period 0 are composed exclusively of the measures of primary caregiver's skills and birth outcomes. The set of observed outcomes for the first and second period are the measures corresponding to the specified factors in addition to the labor supply decision and the wages observed wages. Formally:

$$O_0 = \{\{z_m^{PG}\}_{m=1}^{N_{PG}}, \{z_m^{S_0}\}_{m=1}^{N_{S_0}}\}$$

for t=1,2:

$$O_t = \{h_t^f, h_t^m, a_t, \mathcal{Z}_t\} \cup \underbrace{\{w_t^f\}}_{\text{if } h_t^f>0} \cup \underbrace{\{w_t^m\}}_{\text{if } h_t^m>0}$$

$$\mathcal{Z}_1 = \{\ln(s_1), \ln(\hat{e}_1^f), \ln(\hat{e}_1^m), \ln(\hat{I}_1)\}$$

$$\mathcal{Z}_2 = \{\ln(s_2), \ln(\hat{e}_2^f), \ln(\hat{e}_2^m), \ln(\hat{I}_2), \mu_2\} \tag{40}$$

Note that we only have measures of μ_2 available for the second period. We thus need to integrate over the distribution of the bargaining power in the first period. The exogenous characteristics are given by the age, grades of schooling, age of parents and the distribution factors in E_t.

Given that we need to integrate over the the distribution of the unobserved factors as they are not observed, the expression of the likelihood function becomes a high-dimensional integral with no closed form solution. The natural approach to estimate such likelihood is to approximate the integral via Monte-Carlo methods. That is, drawing shocks from the distribution of the unobserved factors, estimating the likelihood and averaging over these draws. However, note that the time-dependency arising in the production of skills generates an additional difficulty for this approach as for each draw in period 0 we would have to generate multiple draws in the first period and for each draw in the first period we would have to draw multiple draws in the second period. The curse of dimensionality

makes it infeasible to estimate this likelihood with the usual simulation techniques.

A pure simulation strategy to estimate the model would be computationally infeasible. We use particle filtering techniques in order to be able to estimate the model via simulated methods. The full description of the estimation technique altogether with the derivation of the likelihood function are described in Appendix 11.2.

For purposes of estimation, I assume that the preference shocks ϵ_t are distributed according to a normal distribution with no correlation between choices. The unobserved heterogeneity terms, $\eta_{e_t^f}$ also follows a normal distribution. Although I do not allow for correlation between these shocks, I do allow for correlation between the underlying factors in the model (e.g., Pareto weight and skills of mother). The assumption about normality in these terms is not an identifying assumption as I describe in the next section that I can obtain non-parametric identification of such distribution under some independence conditions. The same applies to the error terms in the measurement system of Equation 38. I assume they are distributed according to a normal distribution and that they are independent between each other but this is not an identifying assumption.

6.1 Identification

The identification argument is divided in three parts. First, I show how to the parameters of the measurement system described in 38 are identified. Secondly, I show what variation in the data allows us to recover the distribution of the latent factors. Finally, I show how the parameters of the economic model are recovered.

6.1.1 Measurement System

The general measurement system in a factor model can be written as:

$$Z = \iota_0 + \iota_1 K + \varepsilon \tag{41}$$

where $Z \in \mathbb{R}^M$ contains all the measures available, M is the total number of measurements for all the factors, $K \in \mathbb{R}^{11}$ is the vector of 11 factors and $\varepsilon \in \mathbb{R}^M$ is measurement error. $\iota_1 \in \mathbb{R}^{M \times 11}$ is the matrix of factor loadings. As is common in factor analysis, a location and scale normalizations are necessary to secure identification of the system. The first step is to normalize the first element of ι_1 for each measure to be one, which corresponds to setting

$\iota_{1,1}^k = 1$ for every factor $k \in K$ in Equation 38. The location normalization corresponds to set the mean of each factor to a specified level. The arbitrary scale is set to be:

$$\mathbb{E}[\ln(s_t)] = \mathbb{E}[\ln(PG)] = 0 \text{ for } t = 0, 1, 2$$
$$\mathbb{E}[\mu] = 0.5 \tag{42}$$

I also set normalizations for effort levels and investments that I will explain in full detail in Section 6.1.1. This normalization is irrelevant given that we can re-define new measures $Z - \iota_0$ and the analysis will remain unchanged. From the observed measures Z we can obtain the covariances by noting that:

$$\Sigma_Z = \iota_1 \Sigma_K \iota_1' + \Sigma_\varepsilon \tag{43}$$

where σ_x is the variance covariance matrix of x. Note that we have $M \times (M+1)/2$ moments in order to identify $M \times 11$ factor loadings, $11 \times (11+1)/2$ elements in Σ_k and $M \times (M+1)/2$ elements in Σ_ε. As is often the case in factor analysis, it is necessary to make further assumptions in order to identify the relevant parameters of the model. The normalization $\iota_{1,1}^k = 1$ implies that the number of factor loadings to estimate becomes $M - 11$.

I still need to make further assumptions to recover all the relevant parameters. By making the assumption that the measurement error of the skills at birth is independent of the measurement error of the measures corresponding to the remaining factors, I have enough moments to identify all the parameters. Formally, the assumption is given by $\varepsilon_m^{\ln(s_0)} \perp\!\!\!\perp \varepsilon_{m'}^{k'}$ for $m = 1...N_{ln(s_0)}$, $k \neq \ln(s_0)$, $m' = 1...N_k$. The details of why this is enough to identify the parameters in the measurement system are described in Appendix 11.1.

I can recover ι_m^k for $k \neq \ln(s_0)$ by noting that:

$$\frac{Cov(Z_m^k, Z_1^{\ln(s_0)})}{Cov(Z_1^k, Z_1^{\ln(s_0)})} = \iota_{m,1}^k \tag{44}$$

and the factor loadings of $\ln(s_0)$ are obtained simply by changing the roles of k by $\ln(s_0)$:

$$\frac{Cov(Z_m^{\ln(s_0)}, Z_1^k)}{Cov(Z_1^{\ln(s_0)}, Z_1^k)} = \iota_{m,1}^{\ln(s_0)} \tag{45}$$

6.1.2 Distribution of latent factors

Once the identification of the factor loadings is secured, we can non-parametrically estimate the distribution of the latent factors using a version of Kotlarsky Theorem. Define:

$$ME_j = \{\frac{Z_j^k}{\iota_{j,1}^k}\}_{k \in K} \tag{46}$$

$$me_i = \{\frac{\varepsilon_j^k}{\iota_{j,1}^k}\}_{k \in K} \tag{47}$$

So long as for at least two measures $j = 1, 2$ the following holds:

$$\mathbb{E}\left[me_1 | K, me_2\right] = 0 \tag{48}$$

$$me_2 \perp\!\!\!\perp \theta \tag{49}$$

Theorem 1 in Schennach (2004) provides a non-parametric estimator for the joint density of the latent factors. The theorem notes that the distribution of factors can be expressed as a function of the Fourier transformation of the distribution of measures under the aforementioned assumptions:

$$p(K) = \frac{\int_{-\infty}^{\infty} e^{-i\chi K} e^{\left(\int_0^{\chi} \frac{E\left[iME_1 e^{i\psi ME_2}\right]}{\left[e^{i\psi ME_2}\right]} d\psi\right)} d\chi}{2\pi} \tag{50}$$

once the distribution $p(K)$ has been identified, we can recover the second-order moments $Cov(k, k')$ for any $k, k' \in K$. And once we recover the second-order moments, we can identify the remaining elements of Σ_ε from the system of equations:

$$Cov(Z_m^l, Z_{m'}^{k'}) = \iota_{m,1}^k \iota_{m',1}^{k'} Cov(k, k') + Cov(\varepsilon_m^k, \varepsilon_{m'}^{k'}) \tag{51}$$

6.1.3 Technology of Skill Formation

Since we have secured identification of $p(K)$, we can recover the conditional distribution:

$$p\left(\ln(s_{t+1}) | \ln(s_t), \ln(\tilde{e}_{t+1}^f), \ln(\tilde{e}_{t+1}^m), \ln(\tilde{I}_{t+1}), \mu, \ln(PG)\right) \tag{52}$$

from $p(K)$ for $t = 0, 1$. We can define the following function:

$$s_{t+1} = f_s\left(s_t, \tilde{e}_t^f, \tilde{e}_t^m, \tilde{I}_t^m\right) =$$

$$\mathbb{E}\left[\exp\left(\ln(s_{t+1})|\ln(s_t), \ln(\tilde{e}_{t+1}^f), \ln(\tilde{e}_{t+1}^m), \ln(\tilde{I}_{t+1}), \mu, \ln(PG)\right)\right] \tag{53}$$

where the expectation is taken with respect to the distribution in 52. However, note that we are interested in a function s_{t+1} that has as an additional argument the term η_{s_t} corresponding to heterogeneity. Matzkin (2007) has negative identification results in this case and shows that in order to be able to non-parametrically identify the function we are interested in, we need to impose some restrictions. In particular, if we assume that the term η_{s_t} enters additively in 53 we can trivially identify the production of skills. Additionally, the distribution of η_s is identified as:

$$F_{\left(s_{t+1}|\ln(s_t),\ln(\tilde{e}_t^f),\ln(\tilde{e}_t^m),\ln(\tilde{I}_t^m)\right)}\left(\tilde{s}_{t+1}|\ln(s_t), \ln(\tilde{e}_t^f), \ln(\tilde{e}_t^m), \ln(\tilde{I}_t^m)\right) =$$

$$P\left(s_{t+1} \leq \tilde{s}_{t+1}|\ln(s_t), \ln(\tilde{e}_t^f), \ln(\tilde{e}_t^m), \ln(\tilde{I}_t^m)\right) =$$

$$P\left(f_s\left(s_t, \tilde{e}_t^f, \tilde{e}_t^m, \tilde{I}_t^m\right) + \eta_{s,t} \leq \tilde{s}_{t+1}|\ln(s_t), \ln(\tilde{e}_t^f), \ln(\tilde{e}_t^m), \ln(\tilde{I}_t^m)\right) =$$

$$P\left(\eta_{s,t} \leq \tilde{s}_{t+1} - f_s\left(s_t, \tilde{e}_t^f, \tilde{e}_t^m, \tilde{I}_t^m\right)|\ln(s_t), \ln(\tilde{e}_t^f), \ln(\tilde{e}_t^m), \ln(\tilde{I}_t^m)\right) \tag{54}$$

and thus we can identify the cdf of $\eta_{s,t}$ conditional on factors other than s_{t+1}. With similar arguments we can identify the distribution of the remaining factors.

6.1.4 Preferences

The parameters of the economic model are identified by a combination of exclusion restrictions, exogenous sources of variations and functional form specifications. The main argument used to identify preferences of fathers and mothers follows standard procedures from the literature on collective models of household behavior (Chiappori & Donni, 2009). The use of distribution factors -variables that affect the behavior of the household but do not modify household behavior in any other way- allows us identify preferences for mothers and fathers. The main idea is that variation in such instruments will generate a

movement along the Pareto frontier exclusively generated by the change in the bargaining power. The distribution factors used in this article have been previously used in the literature (Cherchye et al., 2012; Attanasio & Lechene, 2014; Blundell et al., 2005).

First, I describe identification of the Pareto weight function specified in equation 14 because through this function we can separately identify preferences of fathers and mothers. To identify parameters in Λ I use exogenous variation in the gender wage gap, the unemployment gender gap and the sex ratio. The key assumption is that we have enough variation in the data for this factors, and variation is given in a way that is exogenous to the household. Table 22 I report the descriptive statistics of the distribution factors, where we see that there is some variability that is used to secure the identification of the model. Additionally, we impose the exclusion restriction that differences in ages and schooling do not have effect on the behavior on the household other than in the Pareto weight. Finally, we need to have exogenous variation in the share of non-labor income earned by the man to secure identification of all the parameters in Equation 14. I describe how I get such variation in the following paragraph.

The way in which the Chilean social security system schedules monetary transfers to households generates variation in the proportion of income earned by men in the household. The "Social Protection Card"[15] assigns a score to each household corresponding to their socioeconomic status. This score is used as the main targeting device through which monetary transfers are assigned to households, and all subsidies are given to mothers of children whenever there is a child in the household. The amount of the subsidy depends on an additional set of characteristics of the households such as the number of children under 18 living in the household. In 2012, households with a score below 11.734 in the social protection index, and for women who earned less than survey were eligible to receive monetary transfers from the central government. There are seven different programs giving monetary transfers to families in Chile, but the basic ones corresponds to the "Unique Family Subsidies" and "Family Assignments". Under these programs, a mother who earns less than $187,515 CLP and has a score under 11.734 in the Social Protection Card, is eligible to receive a transfer of $7,179 CLP per month, for each child under 18 and for herself. Additionally, families with lower score in the Social Protection Card are eligible for subsidies, all received by the mother, depending on their score, the months they have currently been beneficiary of the programs and the demographic composition of the household.

[15] "Ficha de Proteccion social" in Spanish

The discontinuities in the monetary transfer programs, as well as the variation in elements such as the number of members in the household, gives me variation in the proportion of non-labor income in the hands of women. As we see changes in responses in female empowerment and gender roles questionnaires, associated to these changes, we can identify the extent to which non-labor income affects the process of decision-making within the household.

At this point it is important to make some normalizations about the remaining factors that were not normalized in Section 6.1.1. Effort and investment units do not have natural units. I impose the following normalizations:

$$\mathbb{E}\left[e_t^{f,*} \mid \mu = 0.5, h^f = 1\right] = 1 \tag{55}$$

$$\mathbb{E}\left[I_t^* \mid \mu = 0.5, d = 10\right] = 1 \tag{56}$$

The average effort of fathers in families with a Pareto weight of 0.5 and who participate in the labor market is normalized to one. Similarly, the average investments for families who have a Pareto weight of 0.5 and who have 10 childcare providers within 5 kilometers is normalized to one. Once this normalization is done, we can identify sources of variation in the data that allows us to secure identification of the key parameters.

As we see variation in effort levels in both, fathers and mothers, due to changes in distribution factors, this allows us to identify preferences for children for both parents. For instance, variation in distribution factors might increase the bargaining power of the mother. If we see that effort levels increase as a consequence of the variation in the distribution factors, this gives us information about the relative preferences for children between fathers and mothers. Similarly, changes in investments due to changes in distribution factors allows us to identify the preferences for consumption of mothers and fathers.

Identification of the remaining parameters follow standard arguments in the literature. For the wages, as long as we have enough variation in education and age, we can identify the β coefficients. Similarly, the price elasticity of investments, with respect to the availability of preschool providers $P_{I,1}$, is identified so long as we have variation in the number of preschool providers within five kilometers for households. In Figure 4 we see that we have significant variation in the data regarding this variable. The fact that Chile saw a massive expansion in the number of providers between 2006-2010 gives us significant variation in the data, as the system increased its capacity, measured in the number of children that

the system can provide services for, in 450%. Once the normalization in Equation 56, and with the corresponding variation in childcare providers, we can identify the parameters $P_{I,1}, P_{I,0}$. Similar arguments are used to identify price of childcare.

7 Results

The results of the parameters estimated, altogether with the corresponding standard errors are presented in Tables 23 - 29. As we see, childcare services tend to liberate more time resources from mothers than for fathers. In the same regard, having one additional member in the household decreases the cost of time investments more for mothers than for fathers. We observe that mothers have stronger preferences for children and that fathers find it more costly to spend time with their child than mothers do. Having an additional person in the household helping with childcare or with household chores decreases the utility penalty of investing time in children, more for mothers than for fathers.

Regarding the estimates of the production of skills, we see that there is some evidence of differences in the productivity of time investments of mothers and fathers.. It is not possible to make comparisons between the productivities of different inputs as they are measured in different units (except father's and mother's effort). Nonetheless, we see that monetary investments, childcare attendance, skills of primary caretaker and having adequate birth conditions all seem to have positive effects on the quality of a child. We also observe that availability of childcare services decreases both, the price of childcare and the price of monetary investments in children. This coefficients are estimated with high precision.

Looking at the estimates of the determinants of the Pareto weight, we see there is an effect of the wage ratio on the Pareto weight. This is important as the relationship holds even when we control for differences in education, age and in non labor income. We observe that as the age gap between man and woman decreases, the bargaining power of the man also does. Interestingly, we find a negative relationship between gender ratio, unemployment ratio and wage ratio at the province level and the man's bargaining power.

Regarding the measurement system, we can compute the extent to which each measure contributes to the signal extraction problem. Every measure is contaminated by measurement error and with the estimation results we are able to extract the proportion of the

variance due to true signal and the proportion due to noise.

$$\text{Signal-noise ratio}_{m,k} = \frac{\iota_{m,1}^2 Var(k)}{\iota_{m,1}^2 Var(k) + Var(\varepsilon_m^k)} \tag{57}$$

In Figures 15 - 16, included in the Appendix, I present the signal to noise ratio of the measurement system of the model for measures of effort and investments. We find that cultural activities are the most informative about time investment in children and sharing a meal or performing household chores are within the group of less informative activities. We should be careful with the interpretation of these results: it does not mean that cultural activities are the most productive ones but rather they are the most informative ones. It can certainly be the case that there is an underlying activity that is not reported in the dataset that is performed more often by those parents who perform cultural activities and it is the one that is really productive, not performing cultural activities by itself. Making inferences about which activities are more productive requires more analysis in this point.

7.1 Model fit

The model does a good job when predicting labor force participation and childcare decisions of the household. In Tables 32 and 33 I report the means of labor force participation for both mothers and fathers in 2010 and 2012. The model does a good job in predicting the average levels of participation. Moreover, in Figure 6 compare the predicted and observed levels of female employment by grade of schooling attained. I predict the labor force participation when the terms corresponding to unobserved heterogeneity are located at their mean. The model is able to replicate the gradient in female labor force participation related to education. More educated women participate more in the labor market both in the data and in the simulated results of the model. No significant gradient between education and male labor force is observed in both, the model and the data.

I report the predicted levels of childcare demand and how do they compare with what is observed in the data in Table 34. In Figure **??** I show the predicted and observed demand for childcare services generated. The aggregates for demand of childcare services are reported in Table 34. The model does a good job at predicting the demand of childcare services according to female labor force participation.

The simulated patterns from the model are generated assuming unobserved heterogeneity variables are at their means. An alternative way of reporting the model fit is to generate

draws from their distributions and report the corresponding distribution of model fit. I report the results of such model fit alternative using 200 draws in Figures 8 - 9. As we can see, in both cases the model fits well the data. Finally, the model does a good job at predicting the wages for men and women. Figure 10 I report the estimated distribution of wages for women and men, for both, the predicted ones and the ones observed in the data. I report only the estimated wages for agents who participate in the labor market. The model does a good job not only at predicting the average wage but also the distribution.

With the information about measures and the information from the production of skills, we can get a more precise estimate about the distribution of skills for each individual. The estimated smoothing distribution of skills, which uses all information available in order to make inference about the skills of each individual in sample, is estimated and the results are reported in Figure 11. The details for the construction of the smoothing distribution are presented in Appendix 11.4. The results confirm huge disparities in the skills between rich and poor kids.

8 Evaluating the Effects of Government Programs on the Skills of Young Children

In this section I describe the effects that different policy programs would have on the skills of young children. Additionally, I consider its effects on the female labor force participation and preschool attendance. The policies considered are: 1. increasing the amount of monetary transfers that poor households receive from the central government in the form of subsidies; 2. same as 1. but having father, rather than the mother, as the recipient of such transfers; 3. setting up a system of free childcare services for children older than three and; 4. use the resources of the first policy counterfactual in order to perform in-kind transferences where poor families receive goods that can be used to enhance the skills of young children such as books, toys and puzzles.

Cash transfers are a widely-used program in developing countries. Every country in Latin America has a form of cash transfer that varies by the amount given to the households, and the type of conditions that families need to fulfill in order to be beneficiaries (Fiszbein et al., 2009). Policymakers often invoke the effect of such programs on the promotion of skills of young children, as one of the many benefits of these policies. Moreover, the vast majority of these programs establish that for families with children, the mother

should always be the beneficiary. The main argument for this being that cash in the hands of women Is associated with better child outcomes than cash in the hands of men (Doepke & Tertilt, 2014).

Given the high use of cash transfers as a policy tool in developing countries, and given the explicit condition that transfers go to mothers rather than fathers or other adult members, the first counterfactual policy that I consider is to increase the amount of cash transfers given to mothers of young children. Since 2010, the value of transfers that poor families with children receive have increased significantly. Between 2012 and 2016, families in the lowest quintile of the income distribution, have seen an increase of 72.8%, in real terms, in the cash transfers that they receive from the central government. The details of these programs and how such increase was distributed between various policies are described in Appendix 11.6. Given that governments seem to spend every time more resources in these type of policies, the first counterfactual simulated in this paper consists on doubling the amount of monetary transfers that families located in the lowest quintile of the income distribution receive. Such policy would imply a transfer equivalent to 18% of the average income for families in the the lowest quintile, which corresponds to $23,056 CLP a month.

The Chilean government states explicitly that mothers should be the recipients of such transfers. In order to identify to what extent this condition is justified, and to have an idea if it makes sense to spend additional resources in targeting an individual household member as the recipient of such transfers, rather than any household member, in the second counterfactual I simulate what would happened if we set the father, rather than the mother, as the recipient of the transfers.

Free childcare - preschool policies have also been very popular not only as a way to promote skills in young children but also as a tool to promote female employment. In 2013, the government of Chile established free and mandatory preschool services for children older than five years of age. In part because of that, Chile is now the country with the highest expenditure in preschool education as a share of total government expenditure, of countries in the OECD [16]. Due to the increasing importance of such public policies, in the third counterfactual I simulate the effects of setting up free childcare services for families located in the lowest quintile of the income distribution.

Finally, in the fourth counterfactual I simulate the effects of a system of in-kind transfers where the families receive goods that can potentially increase skills in young children. Al-

[16]Out of the total government expenditures, 2.3% go to the preschool system as opposed to the average of other OECD countries, which is 1.1% (Chile, 2013)

though probably less prevalent than childcare subsidies or cash transfers, in-kind transfes programs are starting to become more popular in developing countries. In Chile, for example, such transfers are being done through the "Chile Crece Contigo"[17] (ChCC) program, established in 2009. ChCC is composed by a set of services for poor families with children younger than five years of age. The goal of the program is to guarantee that every child has the necessary resources so that they can achieve their full developmental potential during childhood. The program offers resources to paren 'ts such as a 24 hours phone line for inquiries about child development, the distribution of books, toys, songs and story books for children, as well as handling learning materials for parents in order to increase their knowledge about the process of child development. ChCC is the most important child development public program currently working in Chile. Due to it's growing importance, I simulate the effect of extending one of ChCC's benefits: that of transfers of goods to improve children's skills such as toys adequate for cognitive stimulation and music material to increase their vocabulary. In the fourth counterfactual I analyze the effects of spending the same amount of resources such as in counterfactual 1 -i.e. $$23,056 CLP a month per family- for families in the lowest income distribution, but doing it in the way of in-kind transfer.

The effects of such policies, on the gaps in skills between children in the highest quintile of the income distribution and children in the lowest quintile, can be found in Figure 12. Initially the gaps in skills between rich and poor children are estimated to approximately of 60% of a standard deviation. We see that in-kind transfers is the most effective policy, decreasing the gaps in 8%. Cash transfers and childcare subsidies have an effect of decreasing this gap in approximately 2%. There are no differences between cash in the hands of women and cash in the hands of men as these two policies have virtually the same effect.

Cash in the hands of women actually increase their bargaining power and women have a stronger say in the household. This can be seen as part of the estimation results of the Pareto weight function reported in Table 31. Additionally, women have stronger preferences for children. However, the two effects combined, increase in their bargaining power and having stronger preferences for children, is not strong enough to seem to justify that it actually makes a difference to target specific members in the household as the sole recipients of monetary transfers from the central government.

The effects of the policies being implemented is decomposed in Tables 35-37. Both cash

[17] Chile Grows with You, in Spanish

transfers and childcare subsidies have effect on employment levels. Cash transfer decreases both, female and male labor force participation in less than percentage point. Childcare subsidies have an effect only in female employment, which is due to the fact that preschool services decreases the penalty of participating in the labor market more for mothers than for fathers. Regarding monetary investments in children, cash transfers and childcare subsidies do not affect significantly this variable. Childcare subsidies increase it for two reasons: first parents spend less resources on preschool fees but additionally mothers participate slightly more in the labor market, increasing the amount of resources available for child investments. However, in kind-transfers have by far the largest effect on monetary investments. This particular mechanism explains most of the reason why in-kind transfer are most effective when it comes to decrease gaps in skills between rich and poor children.

The fact that cash transfers are not very effective at closing the gaps in skills between rich and poor children is consistent with the results form the literature. As pointed out by J. Heckman and Mosso (2014), evidence seems to suggest very limited effect of cash transfers on skills of disadvantaged children. Paxson and Schady (2010) find evaluate a cash transfer program in Ecuador using a random assignment strategy into the treatment. They find that such transfers had no effect on cognitive development for children, except for the poorest where a modest effect is found. However, the authors suggest that the mechanism driving this effect might be through improvement in nutrition and health outcomes. Such mechanism is unlikely to operate in Chile, where the incidence of stunting and wasting in children is below 1% whereas in the sample used by Paxson and Schady (2010) the corresponding proportions are 10% for stunting and 23% for wasting. (Macours, Schady, & Vakis, 2012) find a positive effect of a cash transfer program in Nicaragua. However, the mechanisms suggested by the authors include improvement in nutritional status, which might not necessarily operate in Chile due to the aforementioned reasons, in addition to the fact that the cash transfer program include

8.1 Inefficiency in Child Investments and Female Empowerment

As shown in the preliminary evidence, women spend more time with their children even when controlling for labor supplies. This, together with the evidence that cash in the hands of women translates into better child outcomes than cash in the hands of men, is often used as evidence that women have stronger preferences for children and thus monetary trans-

fers should be given to women if the objective is to invest more in children. Nonetheless, there are different possible explanations why women spend more time with their children than men.

First of all, women's time might be more productive in enhancing skills of children than men's time. If it were the case, the optimal allocation of time in the household would be for women to spend more time with their children without invoking any preferences-based argument. However, in addition to this argument, the relative empowerment of each member might be a plausible explanation. Given that both parents are making investments in a public good (skills of children) and that effort is costly and privately exerted, the fact that women spend more time with children might be a consequence of their relative disempowerment in the household rather than having different preferences in terms of child development[18].

The allocation of time investments is a result of maximizing the skills of children taking into account the cost of exerting these efforts. However, the time cost of each member is not equally weighed, it depends on the relative empowerment of each household member. If the mother is relatively less empowered, the cost of her time is lower than that of the father. This differences in empowerment levels distorts the cost of providing effort and implies inefficiencies in the allocation of resources for children. Put it differently, with the same amount of total effort being provided, we can find an alternative allocation of time investments that would make children better off.

Consider the centralized problem of choosing the effort levels for the second period in order to maximize the skills of children -taking all other inputs as fixed- subject to the fact that the total amount of effort exerted should not exceed the total amount of effort found in the problem of the household described in 20-21. We are basically asking whether or not it is possible to find an alternative allocation of time that would make children better off, whiteout modifying the total amount of effort exerted by both parents. The problem is formally defined as:

$$\max_{e^f, e^m} s_2(e^f, e^m, .) \text{ subject to } e^f + e^m = e^{f,*} + e^{m,*} \tag{58}$$

[18] Doepke and Tertilt (2014) develop a non-cooperative model of household behavior to answer the question of how female empowerment might promote economic development. The authors argue that the reason to develop a non-cooperative model of household behavior lies in the fact that the only mechanism capable of generating differences in investments in children in a collective approach would be that of preferences. However, in this paper I present a collective model of household behavior where differences in investment can arise for a variety of reasons other than preferences.

Define the solution to the problem in 58 as $\left(e^{f,c_1}, e^{m,c_1}\right)$.

Similarly, we can define an alternate centralized problem where we maximize skills subject to the fact that the total time-cost exerted into the production of skills should not exceed that found in the household's problem defined in 1-19. Formally:

$$\max_{e^f, e^m} s_2(e^f, e^m, .) \text{ subject to } c\left(e^f\right) + c\left(e^m\right) = c\left(e^{f,*}\right) + c\left(e^{m,*}\right) \tag{59}$$

Where the cost of effort is given by $c^j(e^j) = \alpha^j_{4,2} e^j (1 + h^j)$. We will call the solution to 59 as $\left(e^{f,c_2}, e^{m,c_2}\right)$. In both cases, for $l = 1, 2$, we do find that:

$$\frac{\left(\frac{e^{f,c_l}}{e^{m,c_l}}\right)}{\left(\frac{e^{f,*}}{e^{m,*}}\right)} \propto \left[\frac{(1-\mu)}{\mu}\right]^{\phi/(1-\phi)} \tag{60}$$

The difference of ratios of effort in the centralized solutions and in the household problem originally defined in 1-19 depends on the Pareto weight and the degree of substitutability between parental efforts. When the Pareto weight heavily favors one member, and if there is some degree of substitutability between parental effort, there would be an inefficient allocation in time investments given that we can find an alternative allocation with the same amount of cost, or the same amount of total effort, that will yield better child outcomes.

It is often argued in the literature that, in a collective model of household behavior, observing different child outcomes when there is a shift in the bargaining power can only be explained by differences in preferences or productivities between parents (Doepke & Tertilt, 2014). Nonetheless, if we take into account that child skills are a public good produced with effort whose cost is privately exerted, shifts in bargaining power can translate in changes in child skills even when parents are identical in terms of preferences and productivities.

This result can be interpreted as an additional argument for female empowerment within households. Not invoking an argument of equality but one of efficiency: disparities in bargaining power lead to inefficient allocations within the household. Taking this into account, and with the estimates of the economic model, we can quantify to what extent the differences observed in time spent with children are due to productivity, preferences or empowerment differences.

9 Conclusions

The fact that skills produced during the first years of life have consequences on outcomes over the life cycle has motivated a significant amount of research directed to analyzing the determinants of the production of cognitive and non-cognitive skills in children. Previous work from Heckman, Todd, Wolpin and coauthors, previously mentioned in this article, have helped us to characterize the way skills are produced during the first years of life. Nonetheless, it is still unclear to see how families decide to invest resources in the corresponding inputs of such production function. This article makes a contribution to the literature of estimating production function of skills in young children nested within a model of household behavior. Although this question has been somewhat addressed in the literature, this paper overcomes some of the limitations faced in previous articles.

The article also makes a contribution in the estimation of collective models of household behavior. The few empirical implementations of these models rely on observing private consumption to fully identify the model. In this case I take into account information about household decision making in order to have an idea of the balance of power within the household. Additionally, I take into account the fact that such observations contain measurement error and thus include a factor analysis framework into the estimation of the economic model.

The results of the paper allows me to simulate the effect of different policies aimed at improving the skills of children. Although monetary transfers are a popular tool in developing countries in their fight against poverty and inequality, the results of this paper suggest that their impact on reducing the gaps of skills between rich and poor children is very limited. On the contrary, conditioning such transfers exclusively on investments that are productive for children has an enormous potential as a policy to reduce the early inequality observed in skills.

10 Figures and Tables

Table 1: 2010 Tests-Measures of child skills

Test	Description	Scoring Interpretation	Ages (in months)	Abbreviation
TEPSI	Psychomotor development test. Three areas of psychomotor development are included: coordination, language and gross motor development. A score including all these areas is also computed.	Higher score indicates a higher level of psychomotor development.	24-60	$MS_{1,10}$-$MS_{3,10}$
CBCL	Child Behavior Checklist. This tool gives a general diagnosis of the socioemotional development of children in seven dimensions: Emotional intelligence, Anxiety-depression, Somatic complaints, Isolation, sleeping disorders, aggressive behaviors and attention deficit.	A higher score indicates more persistence of behavioral problems.	18-60	$MS_{5,10}$-$MS_{11,10}$

Table 2: 2012 Tests-Measures of child skills

Test	Description	Scoring Interpretation	Ages (in months)	Abbreviation
TADI	Test of Early Childhood Learning. 4 dimensions including cognition, motor skills, language and socio-emotional development. For each one, two scores are computed: raw and total.	Higher scores indicate higher levels of childhood development	6-84	$MS_{1,12}$-$MS_{4,12}$
BATELLE	Batelle Instrument for Child Develpoment. Five dimensions of child development in addition to a total-comprehensive child development score	Higher score indicates a higher level of child development .	6-84	$MS_{5,12}$-$MS_{10,12}$
TVIP	Peabody Picture Vocabulary Test. A raw score as well as a standardized score is computed.	Higher scores indicate higher levels of verbal intelligence for children	30-84	$MS_{13,12}$

Table 3: Description of sample used in the analysis

Filter	Number of households
Initial sample	18,310
Household not surveyed in 2012	16,033
Household not surveyed in 2010	12,898
Parent not living in household	7,855
Siblings within five years of age in the household	4,125
Children with incomplete skills questionnaires	2,247
Households with incomplete questionnaires	950

Table 4: Descriptive statistics - Families in 2012

Variable	Mean	25%	75%	Sd
Mother's age	34.52	29.00	39.00	6.94
Father's age	37.41	32.00	43.00	7.96
Mother's years of schooling	11.27	10.00	12.00	2.97
Father's years of schooling	10.72	8.00	12.00	3.13
Mother's hours of work (week)	24.22	0.00	45.00	21.34
Father's hours of work (week)	43.20	45.00	48.00	16.03
Mother's weekly wage (1,000 CLP)	82.73	41.86	95.24	92.78
Mother's weekly wage (USD)	165.46	83.72	190.49	185.55
Father's weekly wage (1,000 CLP)	85.48	42.62	93.02	88.19
Father's weekly wage (USD)	170.95	85.23	186.05	176.39
Household's total Income (Weekly-CLP)	124.55	59.88	151.16	108.83
Household's total Income (Weekly (USD))	249.10	119.76	302.33	217.66
Age of child (months)	64.60	58.00	72.00	8.40

Table 5: **Age distribution (2012)**

Item	Number	Per cent
4	310	32.63
5	397	41.79
6	243	25.58
Total	950	100.00

Table 6: Measures used for parental effort in 2012

Abbreviation	Activity
$MS1_{EF,12}$	Reads Children's storybooks or drawing books
$MS2_{EF,12}$	Tells her stories
$MS3_{EF,12}$	Sings to child
$MS4_{EF,12}$	Takes her to parks
$MS5_{EF,12}$	Takes her to museums, zoos, libraries or other cultural activities
$MS6_{EF,12}$	Spends time with her chatting or drawing
$MS7_{EF,12}$	Invites her to participate in household chores
$MS8_{EF,12}$	Takes her to the supermarket
$MS9_{EF,12}$	Shares a meal with her
$MS10_{EF,12}$	Teaches the animals and their sounds
$MS11_{EF,12}$	Teaches her the colors
$MS12_{EF,12}$	Goes with her to visit friends or family members
$MS13_{EF,12}$	Teaches her the numbers and how to count
$MS14_{EF,12}$	Teaches her words

For each question parents reply how often, during the last seven days, they perform each activity. The possible answers are: Never, 1-3 times, 4-6 times.

Table 7: Measures used for parental effort in 2010

Abbreviation	Activity
$MS1_{EF,10}$	Reads Childre's storybooks or drawing books
$MS2_{EF,10}$	Tells her stories
$MS3_{EF,10}$	Sings to her
$MS4_{EF,10}$	Takes her to parks
$MS5_{EF,10}$	Takes her to museums, zoos, libraries or other cultural activities
$MS6_{EF,10}$	Plays with her
$MS7_{EF,10}$	Spends time with her talking or drawing

Table 8: Measures used for Skills in 2012

Abbreviation	Outcome
$MS1_{12}$	TADI-Cognitive subdomain
$MS2_{12}$	TADI-Motor skills subdomain
$MS3_{12}$	TEPSI-Motor skills subdomain
$MS4_{12}$	TADI-Language subdomain
$MS5_{12}$	Battelle-I
$MS6_{12}$	Battelle-II
$MS7_{12}$	Battelle-III
$MS8_{12}$	Battelle-IV
$MS9_{12}$	Battelle-V
$MS10_{12}$	Battelle-T
$MS11_{12}$	PPVT-Vocabulary Test

All test scores are standardized to be mean zero and variance one.

Table 9: Measures used for Skills in 2010

Abbreviation	Outcome
$MS1_{10}$	TEPSI-Coordination subdomain
$MS2_{10}$	TEPSI-Language subdomain
$MS3_{10}$	TEPSI-Motor skills subdomain
$MS4_{10}$	CBCL-Emotional intelligence
$MS5_{10}$	CBCL-anxiety -depression
$MS6_{10}$	CBCL-somatic complaints
$MS7_{10}$	CBCL-Isolation
$MS8_{10}$	CBCL-Sleeping disorder
$MS9_{10}$	CBCL-Attention deficit
$MS10_{10}$	CBCL-Aggressive behavior

All test scores are standardized to be mean zero and variance one.

Table 10: Measures used for Skills at birth

Abbreviation	Outcome
$MS1_{BIRTH}$	Mother diagnosed with Preeclampsia during pregnancy
$MS2_{BIRTH}$	Mother diagnosed with Cholestasis during pregnancy
$MS3_{BIRTH}$	Mother diagnosed with Urinary infections during pregnancy
$MS4_{BIRTH}$	Mother diagnosed with Hemorrages during pregnancy
$MS5_{BIRTH}$	Mother diagnosed with Hipertension during pregnancy
$MS6_{BIRTH}$	Mother diagnosed with Placenta Previa during pregnancy
$MS7_{BIRTH}$	Mother diagnosed with Diabetes G during pregnancy
$MS8_{BIRTH}$	Mother diagnosed with Anemia during pregnancy
$MS9_{BIRTH}$	Mother diagnosed with Toxoplasmosis during pregnancy
$MS10_{BIRTH}$	Mother diagnosed with Depression during pregnancy
$MS11_{BIRTH}$	Mother diagnosed with Bipolar D. during pregnancy
$MS12_{BIRTH}$	Mother diagnosed with Anxiety D. during pregnancy
$MS13_{BIRTH}$	Mother diagnosed with Obsesive compulsive D. during pregnancy
$MS14_{BIRTH}$	Mother diagnosed with Fobia during pregnancy
$MS15_{BIRTH}$	Mother diagnosed with Panic D. during pregnancy
$MS16_{BIRTH}$	Mother diagnosed with PTSD during pregnancy
$MS17_{BIRTH}$	Cigarrettes consumed during pregnancy
$MS18_{BIRTH}$	Cigarrettes consumed during the first six months of life of child
$MS19_{BIRTH}$	Alcohol consumption during pregnancy*
$MS20_{BIRTH}$	Substance abuse during pregnancy*
$MS21_{BIRTH}$	Child was born pre-term
$MS22_{BIRTH}$	Weight at birth (grams)
$MS23_{BIRTH}$	Height at birth (cm)

*Possible answers are never (0), rarely (1) and often (2).

Table 11: Measures used for Skills of primary caregiver

Abbreviation	Outcome
$MS1_{PG}$	WAIS-Numerical test
$MS2_{PG}$	WAIS-Vocabulary test
$MS3_{PG}$	BFI-Agreeableness
$MS4_{PG}$	BFI-Openness
$MS5_{PG}$	BFI-Extroversion
$MS6_{PG}$	BFI-Neuroticism
$MS7_{PG}$	BFI-Conscientiousness

All test scores are standardized to be mean zero and variance one.

Table 12: Measures used for Investments in 2010

Abbreviation	Question
$MS1_{INV,10}$	Child has a special place where to store toys and belongings
$MS2_{INV,10}$	Child has at least one toy that involves muscular activity
$MS3_{INV,10}$	Child has toys to pull and push
$MS4_{INV,10}$	Child has at least one toy with wheels
$MS5_{INV,10}$	Availability of plush toys-stuffed animals
$MS6_{INV,10}$	Availability of mobiles for child
$MS7_{INV,10}$	Availability of musical or literary toys
$MS8_{INV,10}$	Child has three or more books of his own

Table 13: Measures used for Investment in 2012

Abbreviation	Outcome
$MS1_{INV,12}$	Consumption of hamburger-pizza-fries*
$MS2_{INV,12}$	Consumption of Fish-Beef-Chicken*
$MS3_{INV,12}$	Consumption of bread-rice-pasta
$MS4_{INV,12}$	Consumption of legumes*
$MS5_{INV,12}$	Consumption of Chocolate-Candy*
$MS6_{INV,12}$	Consumption of juice*
$MS7_{INV,12}$	Consumption of snacks in bags*
$MS8_{INV,12}$	Consumption of milk*
$MS9_{INV,12}$	Consumption of water*
$MS10_{INV,12}$	Consumption of cookies*
$MS11_{INV,12}$	Consumption of fruits and vegetables*
$MS12_{INV,12}$	There are two or more toys in the household where child can learn colors, sizes and shapes
$MS13_{INV,12}$	Child has three or more puzzles
$MS14_{INV,12}$	There is a music device where child can listen children's music
$MS15_{INV,12}$	There are two or more toys for free expression or impersonations such as tools and customs
$MS16_{INV,12}$	There are two or more toys in the household that can help with learning numbers
$MS17_{INV,12}$	There are at least ten children's books available in the house
$MS18_{INV,12}$	There are at least ten books for adults
$MS19_{INV,12}$	At first sight, there is very little evidence that there is a child living in the household
$MS20_{INV,12}$	Number of people with whom child shares bed
$MS21_{INV,12}$	Number of people with whom child shares room

*: The possible answers are 1: never, 2: one to two times a month; 3: one to three times a week;
4: four to six times a week; 5: once a day; 6: two or more times a day.

Table 14: Measures used for Pareto weight

Abbreviation	Question
$MS1_{BARG}$	A woman who is in charge of most part of tasks of the household has no time to work*
$MS2_{BARG}$	Both spouses should contribute to household income*
$MS3_{BARG}$	It is better for everyone if the man goes to work and the woman takes care of the household and the family*
$MS4_{BARG}$	Men should assume a more active role in the household chores and childcare than what they actually do*
$MS5_{BARG}$	If my spouse earned enough there is no reason for me to work*
$MS6_{BARG}$	After having children, the best for a woman is to develop her carreer*
$MS7_{BARG}$	Taking into account the pros and cons, it is very important for me to have a paying job*
$MS8_{BARG}$	Having a payed job is the best way for a woman to become independent*
$MS9_{BARG}$	Father's and mother's time is equally important for the children*
$MS10_{BARG}$	It is better to have a bad marriage than to remain single*
$MS11_{BARG}$	Woman participates in the process of administering income (yes-no)
$MS12_{BARG}$	Man participates in the process of administering income (yes-no)
$MS13_{BARG}$	Both, father and mother participate in the process of administering income (yes-no)
$MS14_{BARG}$	(Mother) Who should take care of children (Father-Mother-Both-Other)
$MS15_{BARG}$	(Man) Women should only be in charge of taking care of children (yes-no)
$MS16_{BARG}$	(Man) Women should take care of children and work part time (yes-no)
$MS17_{BARG}$	(Man) Women should work full-time and delegate childcare to someone else (yes-no)
$MS18_{BARG}$	(Man) Men are better at childcare than women (yes-no)

*: For each question the woman provides an answer between 1 to 5 with the following scale:
Disagrees very much; disagrees; doesn't know; agrees; agrees very much.

Table 15: Father's opinion on gender roles

Item	Number	Per cent
Women should only spend time taking care of chidlren	282	30
Women should take care of children and work if there is remaining time	611	64
Women should work full time	52	5
Men take care better of children than women	5	1
Total	950	100

Table 16: Summary statistics-Measures of bargaining power

Variable	**Mean**	**(Std. Dev.)**
A woman in charge of chores should not work	2.62	(0.82)
Both parents should contribute equally to household income	1.76	(0.62)
It is better if the man goes to work and the woman stays at home	2.52	(0.82)
Men should be more involved in household chores	1.75	(0.66)
If husband earned enough there is no reason for woman to work	2.19	(0.88)
It is better if woman has children after having a succesful carreer	2.36	(0.81)
It is very important for a woman to have a job	1.81	(0.66)
Having a job is the best way for a woman to achieve independence	1.79	(0.66)
Father's time is as important as mother's time for children	1.49	(0.61)
It is better to have a bad marriage than being single	3.3	(0.73)
N	950	

All questions are answered by the mother of the child. The possible answers are 1: strongly agrees; 2: agrees; 3: disagrees; 4: strongly disagrees.

Table 17: Time investments and labor supply (2010)

	(1)	(2)
VARIABLES	Mother's effort	Father's effort
Mother: hours worked weekly	-0.01**	0.01*
	(0.01)	(0.01)
Father: hours worked weekly	0.03***	-0.00
	(0.01)	(0.01)
Observations	1,035	1,035
Adjusted R-squared	0.05	0.05

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The measure of effort is constructed via Principal component analysis, extracting one factor for the variables used as measures of time investments by parents. The measures of parental effort, altogether with the BFI, Wais and PSI test scores are all standardized to have mean zero and one standard deviation.

Table 18: Time investments and labor supply (2012)

VARIABLES	(1) Mother's effort	(2) Father's effort
Mother: hours worked weekly	0.00	0.01***
	(0.00)	(0.00)
Father: hours worked weekly	-0.00	-0.01**
	(0.00)	(0.00)
Observations	1,035	1,035
Adjusted R-squared	0.04	0.05

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The measure of effort is constructed via Principal component analysis, extracting one factor for the variables used as measures of time investments by parents. The measures of parental effort, altogether with the BFI, Wais and PSI test scores are all standardized to have mean zero and one standard deviation.

Table 19: Child outcomes in 2010 and share of income earned by women

VARIABLES	(1) TEPSI language test	(2) Emotional reactions (CBCL 1)+	(3) Aggresive behavior (CBCL 7)+
Mother's income share	0.31**	-0.25*	-0.24*
	(0.15)	(0.14)	(0.13)
Total household income	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)
Mother's years of schooling	0.03**	-0.02	0.01
	(0.01)	(0.02)	(0.01)
Father's years of schooling	0.01	-0.03**	-0.05***
	(0.01)	(0.01)	(0.01)
Childcare	0.29***	0.10	0.07
	(0.08)	(0.07)	(0.07)
Number of siblings	-0.01	-0.06*	-0.07**
	(0.03)	(0.03)	(0.03)
Age of child (months)	0.01***	0.00	-0.00
	(0.00)	(0.00)	(0.00)
BFI-Kindness	0.05	-0.04	-0.07**
	(0.04)	(0.04)	(0.04)
BFI-Openness	0.00	-0.03	-0.05
	(0.04)	(0.03)	(0.03)
BFI-Extraversion	0.04	-0.07**	-0.00
	(0.04)	(0.03)	(0.04)
BFI-Neuroticism	0.03	0.23***	0.27***
	(0.03)	(0.04)	(0.03)
BFI-Responsibility	-0.00	0.04	-0.06*
	(0.04)	(0.03)	(0.04)
Wais-digits	0.11***	-0.04	-0.08**
	(0.03)	(0.03)	(0.03)
Wais-Vocabulary	0.09**	-0.13***	0.02
	(0.04)	(0.03)	(0.04)
Observations	950	950	950
Adjusted R-squared	0.13	0.17	0.15

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 20: Child outcomes in 2012 and share of income earned by women

VARIABLES	(1) Motor skills 2 (B3)	(2) Cognitive test (B5)	(3) Batelle Total
Mother's income share	0.44***	0.28**	0.34**
	(0.15)	(0.14)	(0.15)
Total household income	-0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)
Mother's years of schooling	0.01	0.01	0.02
	(0.02)	(0.02)	(0.01)
Father's years of schooling	0.01	0.03**	0.03**
	(0.01)	(0.01)	(0.01)
Number of siblings	0.03	0.04	0.05
	(0.04)	(0.04)	(0.04)
Age of child (months)	0.00	0.00	0.01*
	(0.00)	(0.00)	(0.00)
BFI-Kindness	0.05	0.13***	0.07*
	(0.04)	(0.04)	(0.04)
BFI-Openness	0.06	0.04	0.07**
	(0.04)	(0.03)	(0.04)
BFI-Extraversion	-0.00	0.03	-0.01
	(0.04)	(0.04)	(0.04)
BFI-Neuroticism	0.04	-0.02	0.03
	(0.04)	(0.04)	(0.03)
BFI-Responsibility	0.04	-0.04	-0.04
	(0.04)	(0.03)	(0.03)
Wais-digits	0.05	0.08**	0.10***
	(0.04)	(0.03)	(0.03)
Wais-Vocabulary	0.04	-0.01	0.04
	(0.04)	(0.04)	(0.04)
Observations	950	950	950
Adjusted R-squared	0.03	0.05	0.08

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Additional controlsi include age of child, race, age of both parents, test scores of primary caregiver and number of siblings. +: lower scores indicate lower incidence of behavioral problems.

Table 21: Female empowerment and Child outcomes

VARIABLES	(1) Toys for development	(2) Fruits and vegetables	(3) Bread	(4) Cookies and candies	(5) People sharing bedroom with child
Total household income ($1,000 CLP)	0.00	-0.00	0.00	0.00	-0.05***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Mother's years of schooling	0.01*	0.05***	0.02	0.00	-0.03**
	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Father's years of schooling	0.01	-0.02	-0.00	0.00	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Number of siblings	0.02	-0.08*	-0.01	-0.12***	0.07*
	(0.02)	(0.05)	(0.04)	(0.04)	(0.04)
People in household	-0.03**	0.07**	0.01	0.10***	0.19***
	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Woman administers+	0.09***	0.13**	-0.14**	0.20***	-0.07
	(0.03)	(0.07)	(0.06)	(0.06)	(0.06)
Gender roles -Woman++	-0.00	-0.05	-0.02	-0.06	0.08**
	(0.02)	(0.04)	(0.04)	(0.04)	(0.04)
Gender roles - Man++	-0.02	-0.01	-0.08	-0.06	-0.00
	(0.04)	(0.08)	(0.07)	(0.07)	(0.07)
Observations	950	950	950	950	950
Adjusted R-squared	0.03	0.04	0.01	0.02	0.19

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Consumption of bread, fruits and vegetables and cookies and candies is related to the frequency of consumption of this food on a weekly basis. More details can be found in Table 13. + dummy variable indicating whether the mother is the person in charge of administering the resources of the household (1) or no (0). ++ opinion of gender roles according to the man and the woman. A value of one indicates that the person agrees with the sentence "Women should not work and should only take care of children".

Table 22: Summary statistics-Variables determining Pareto weight

Variable	Mean	(Std. Dev.)
Father's non-labor income share	0.28	(0.35)
Age difference (Father-Mother)	2.89	(5.19)
Difference in grades attained (Father-Mother)	-0.55	(2.84)
Sex ratio in region (Women/Men)	1	(0.07)
Unemployment ratio in region (Men/Women)	0.67	(0.11)
Wage ratio in region (Men/Women)	1.21	(0.07)
N	950	

The ratio of wages offered is not reported in these table as is the results of the parameters estimated in the model.

Table 23: Estimates: Utility function. Mother's preferences

Parameter	Estimate	Standard Error
$\alpha^m_{1,12}$	0.6312	0.0028
$\alpha^m_{2,12}$	0.0517	0.0001
$\alpha^m_{3,12}$	0.3035	0.2208
$\alpha^m_{4,0,12}$	0.0136	0.0001
$\alpha^m_{4,1,12}$	0.0012	0.0001
$\alpha^m_{1,10}$	0.0554	0.0003
$\alpha^m_{2,10}$	0.0038	0.0001
$\alpha^m_{3,10}$	0.1026	0.2437
$\alpha^m_{4,0,10}$	0.0001	0.0001
$\alpha^m_{4,1,10}$	0.0001	0.0001
$\alpha^m_{5,10}$	0.8381	0.3831

Table 24: Estimates: Utility function. Father's preferences

Parameter	Estimate	Standard Error
$\alpha^f_{1,12}$	0.1587	0.0026
$\alpha^f_{2,12}$	0.0339	0.0001
$\alpha^f_{3,12}$	0.8042	0.3610
$\alpha^f_{4,0,12}$	0.0032	0.0001
$\alpha^f_{4,1,12}$	0.0016	0.0001
$\alpha^f_{1,10}$	0.6157	0.0026
$\alpha^f_{2,10}$	0.1407	0.0005
$\alpha^f_{3,10}$	0.8042	0.4496
$\alpha^f_{4,0,10}$	0.0114	0.0001
$\alpha^f_{4,1,10}$	0.0001	0.0001
$\alpha^f_{5,10}$	0.0057	1.0415

Table 25: Estimates: Preference shock

Parameter	Estimate	Standard Error
$\sigma^m_{W,A}$	3.6627	0.8352
$\sigma^m_{NW,A}$	0.9095	0.1140
$\sigma^m_{NW,NA}$	0.0794	0.2469
$\sigma^f_{W,A}$	0.5020	0.4519
$\sigma^f_{NW,A}$	0.0851	0.4550
$\sigma^f_{NW,NA}$	0.0020	0.0777

Preference shocks for work-no childcare are standardized to zero

Table 26: Estimates: Mothers wages

Parameter	Estimate	Standard Error
β^m_0	5.7874	0.4394
β^m_1	0.2757	0.0251
β^m_2	0.0732	0.0379
β^m_3	-0.0006	0.0006
σ_{w_m}	0.8280	0.0606

Table 27: Estimates: Fathers wages

Parameter	Estimate	Standard Error
β^f_0	5.8103	0.2997
β^f_1	0.1260	0.0055
β^f_2	0.1875	0.0156
β^f_3	-0.0022	0.0002
σ_{w_f}	0.6894	0.0130

Table 28: Estimates: Production of Skills

Parameter	Estimate	Standard Error
θ_0	0.2128	0.0011
θ_1	0.2673	0.0017
θ_2	0.5199	0.0032
ϕ	0.4688	0.0007
γ_f	0.3647	0.0006
γ_m	0.6353	0.0016
δ_0	-0.8000	0.0051
δ_1	-0.0000	0.0001
δ_2	0.0010	0.0004
$\delta_{3,10}$	3.5038	0.0172
$\delta_{3,12}$	5.3000	0.0408
δ_4	0.0130	0.0001
σ_s	1.5754	0.0065

Table 29: Estimates: Distribution of latent factors

Parameter	Estimate	Standard Error
σ_{ef}^m	2.5133	0.0039
σ_{ef}^f	3.3754	0.0025
σ_{inv}	2.1896	0.0144

Table 30: Estimates: Prices

Parameter	Estimate	Standard Error
Price_{I_0}	966.2378	1.8225
Price_{I_1}	1.0537	0.0019
Pchildcare_0	2440.6020	1.1684
Pchildcare_1	622.6098	1.2417

Table 31: Estimates: Pareto weight

Parameter	Estimate	Standard Error	Description
λ_0	-2.7321	0.0136	Intercept
λ_1	0.0023	0.0143	Wage ratio
λ_2	0.0527	0.0006	Non-labor income ratio
λ_3	-0.1194	0.0001	Age difference
λ_4	0.0036	0.0026	Educational difference
λ_5	-2.5325	0.0039	Gender ratio
λ_6	-0.0069	0.0328	Unemployment ratio
λ_7	-0.7722	0.0006	Wage ratio (region)
σ_μ	0.5179	0.0074	Standard deviation

Table 32: Model Fit - I

Female Labor Force Participation	Predicted	Data
2010	57.2%	60.28%
2012	62.6%	61.47%

Table 33: Model Fit - II

Male Labor Force Participation	Predicted	Data
2010	91.8%	94.6%
2012	96.1%	93.2%

Table 34: Model Fit - III

Childcare Attendance	Predicted	Data
Working Mothers	68.4%	67.7%
Not-working Mothers	41.6%	42.9%

Table 35: Effects of Policy counterfactuals. Change in Female employment (percentage points)

Counterfactual	Effect on Female employment
1	-0.63
2	-0.63
3	0.63
4	0.00

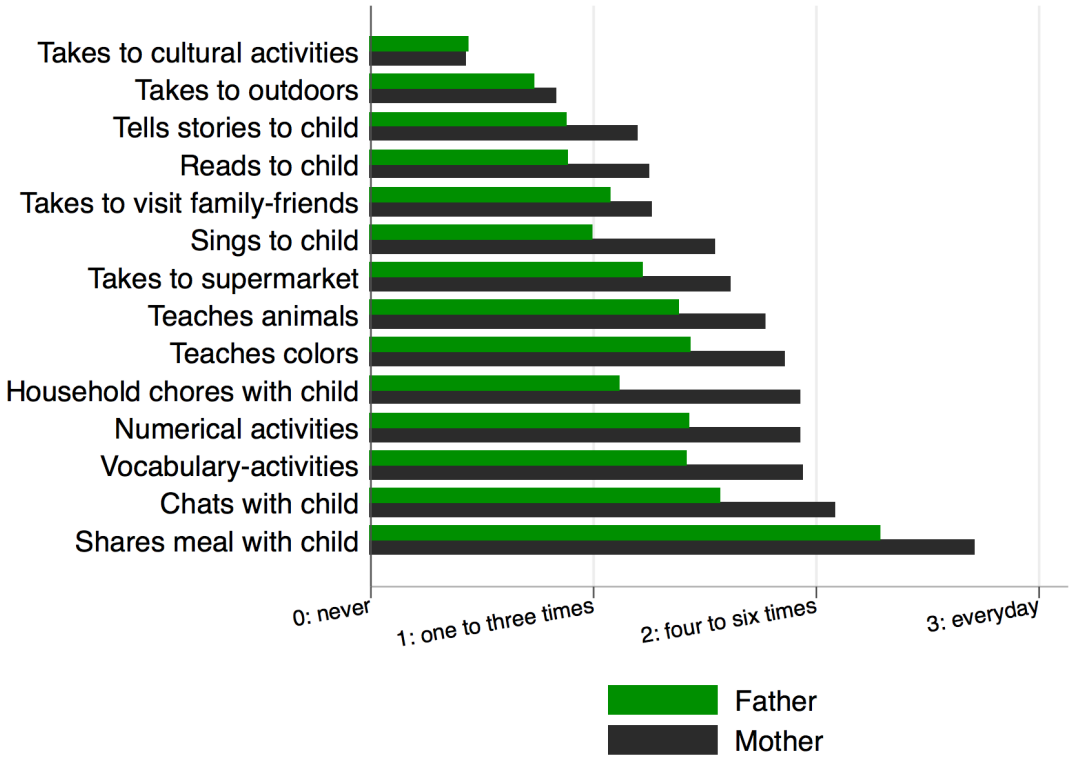
Table 36: Effects of Policy counterfactuals. Change in Male employment (percentage points)

Counterfactual	Effect on Male employment
1	-0.21
2	-0.21
3	0.00
4	0.00

Table 37: Effects of Policy counterfactuals. Change in Money invested

Counterfactual	Change in Money Invested
1	11.36
2	11.36
3	34.08
4	333.59

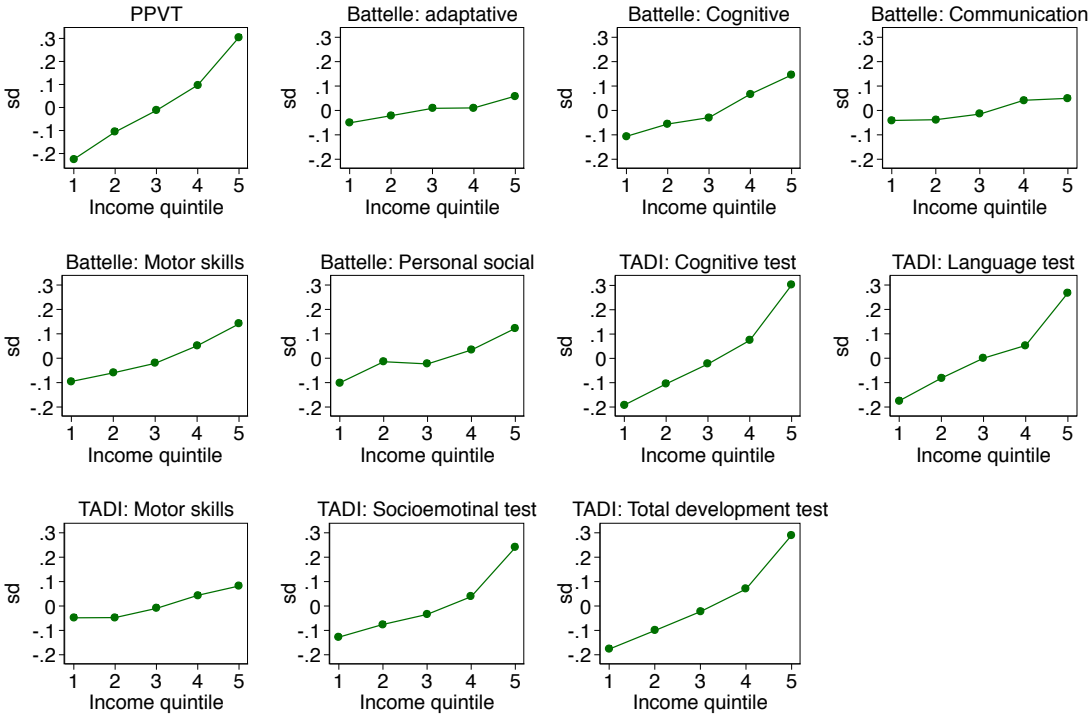
Figure 1: Weekly frequency of activities between parents and children



For each activity there are possible answers: 0: never, 1: one to three times a week; 2: four to six times a week; 3: everyday.

Figure 2: Gaps in health at birth (%)

Figure 3: Gaps in skills at age 5



All test scores and parental assessments are normalized to have mean zero and variance one. PPVT stands for Peabody Picture Vocabulary Tests. Battelle is an instrument containing different scales to measures development of children. TADI is a test of learning and child development[a]. In all tests, differences between the scores of children in the lowest quintile of the income distribution is statistically different to those children who are in the highest quintile of the income distribution except for: TADI motor skills and Battelle adaptative.

[a] "Test de Aprendizaje y Dessarollo Infantil" in Spanish.

Figure 4: Information on Preschool Providers

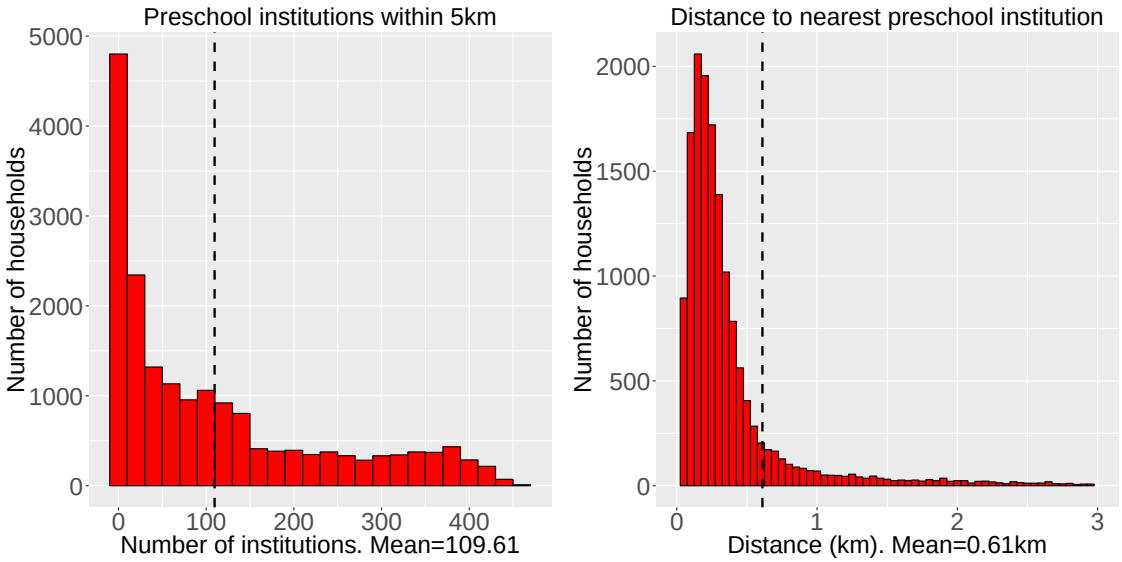


Figure 5: Example of distribution of childcare providers. City of "La Serena", Chile

Figure 6: Model fit: Female labor force participation according to education

Figure 7: Model fit: Male labor force participation according to education

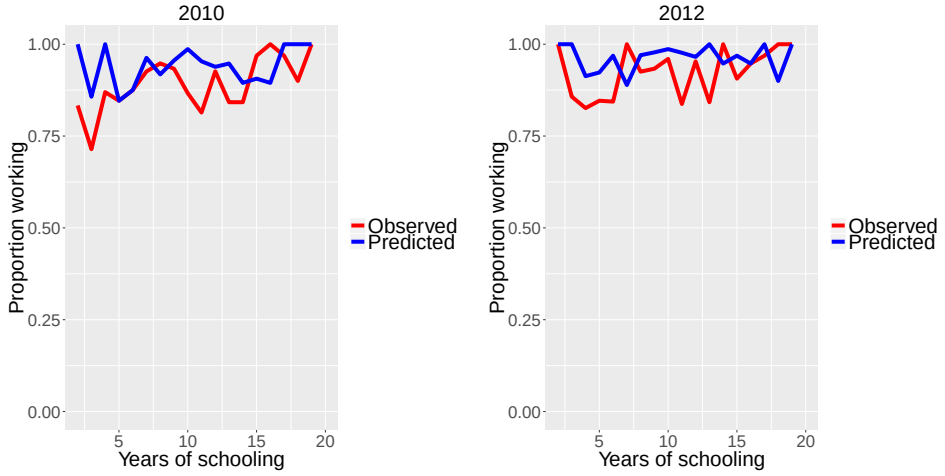
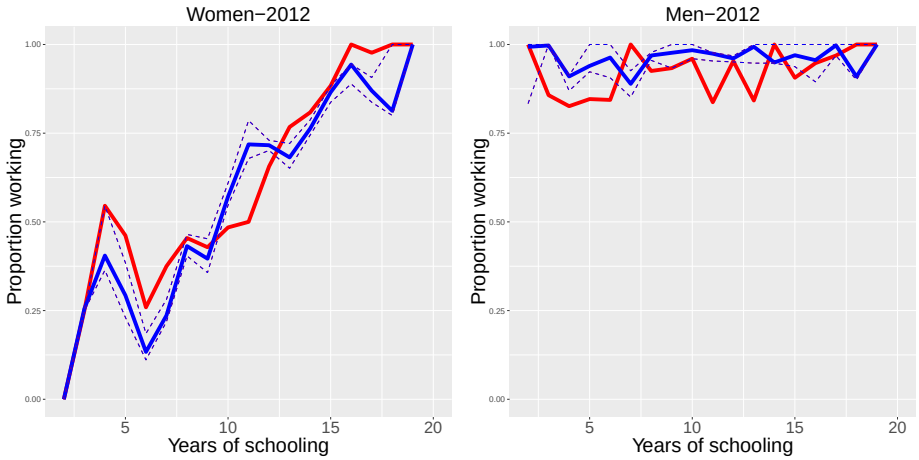
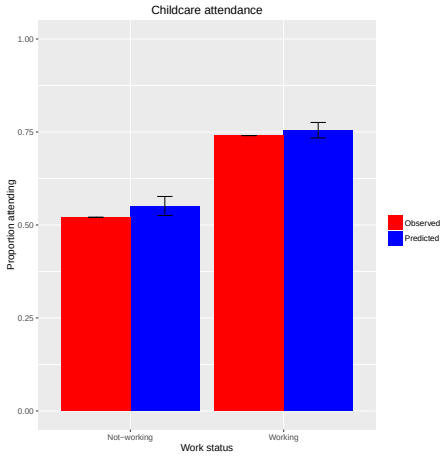


Figure 8: Bootstrap fit: Parents' Labor Force Participation in 2012



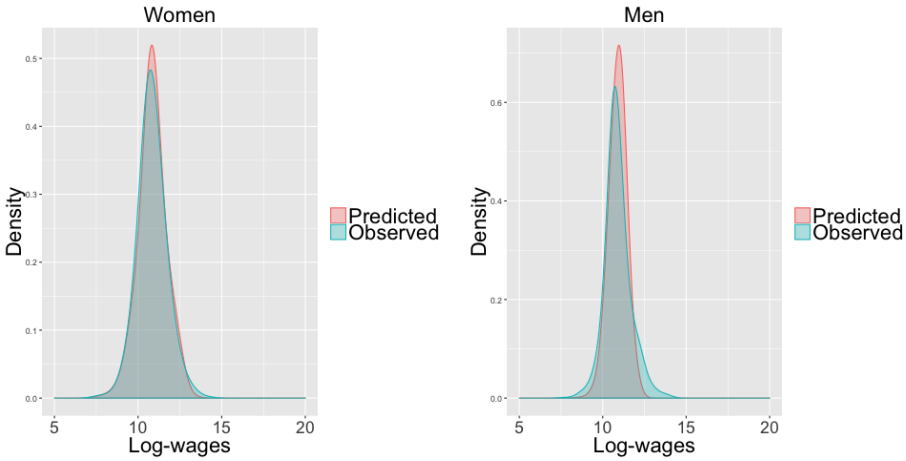
Dashed lines represent the 95% confidence interval

Figure 9: Bootstrap fit: Childcare decisions (%)



Brackets include the 95% confidence interval

Figure 10: Model fit: distribution of wages



Kernel density estimates of predicted and observed wages. Bandwidth chosen is 3.

Figure 11: Distribution of skills. Smoothing distribution

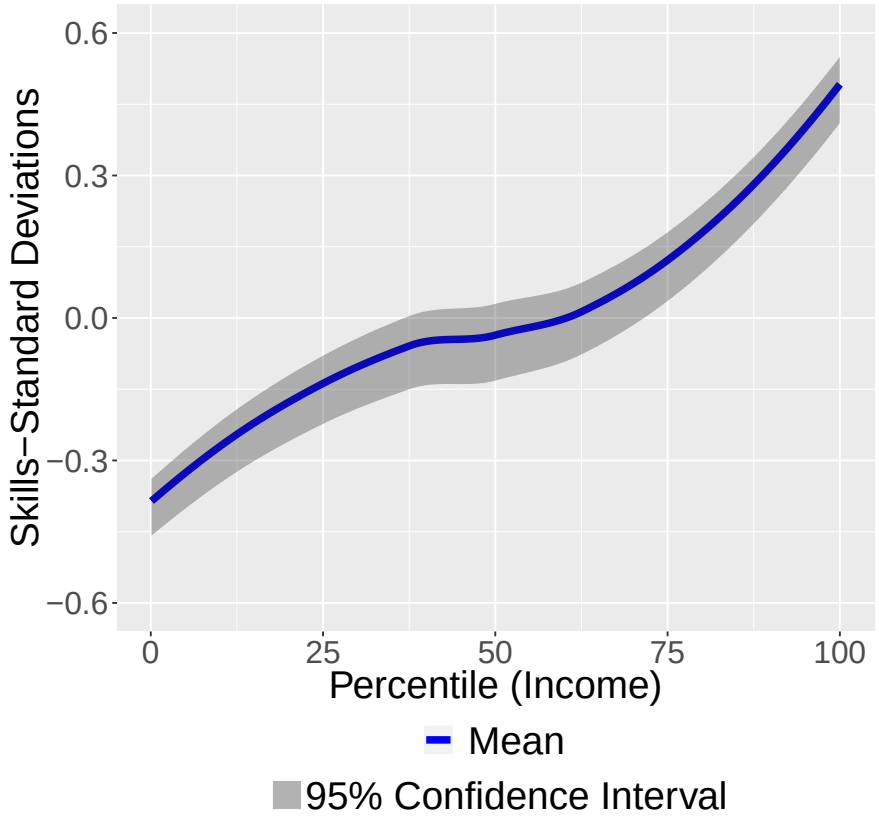
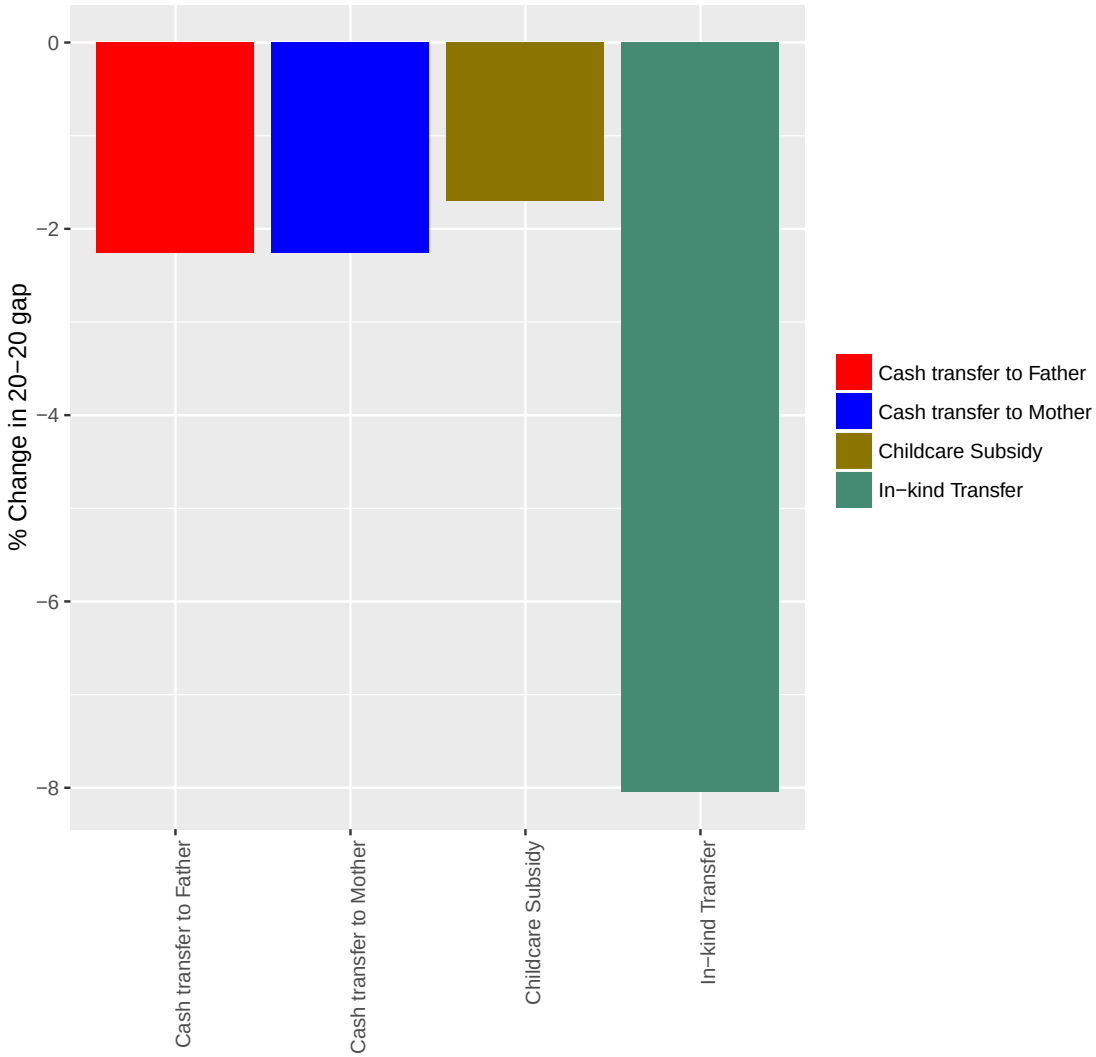


Figure 12: Effects of Policy Interventions

Effects on the gap in skills between the top 20% richest households and the poorest 20% of the households



References

Attanasio, O. P., & Lechene, V. (2014). Efficient responses to targeted cash transfers. *Journal of Political Economy*, *122*(1), 178–222.

Basu, K. (2006). Gender and say: a model of household behaviour with endogenously determined balance of power*. *The Economic Journal*, *116*(511), 558–580.

Bernal, R. (2008). The effect of maternal employment and child care on children's cognitive development. *International Economic Review*, *49*(4), 1173–1209.

Blundell, R., Chiappori, P.-A., & Meghir, C. (2005). Collective labor supply with children. *Journal of political Economy*, *113*(6), 1277–1306.

Bobonis, G. J. (2009). Is the allocation of resources within the household efficient? new evidence from a randomized experiment. *Journal of political Economy*, *117*(3), 453–503.

Borghans, L., Duckworth, A. L., Heckman, J. J., & Ter Weel, B. (2008). The economics and psychology of personality traits. *Journal of human Resources*, *43*(4), 972–1059.

Browning, M., Chiappori, P.-A., & Lewbel, A. (2013). Estimating consumption economies of scale, adult equivalence scales, and household bargaining power. *The Review of Economic Studies*, rdt019.

Browning, M., Chiappori, P.-A., & Weiss, Y. (2014). *Economics of the family*. Cambridge University Press.

Bruins, M. (2015). Taxes, welfare and the resources parents allocate to children. *Unpublished manuscript*.

Carneiro, P., Hansen, K., & Heckman, J. (2003). Estimating distributions of treatment effects with an application to the returns to schooling and measurement of the effects of uncertainty on college choice. *International Economic Review*, *44*(2), 361-422.

Cesarini, D., Lindqvist, E., Notowidigdo, M. J., & Ostling, R. (2013). *The effect of wealth on household labor supply: Evidence from swedish lotteries.*

Cherchye, L., De Rock, B., & Vermeulen, F. (2012). Married with children: A collective labor supply model with detailed time use and intrahousehold expenditure information. *The American Economic Review*, *102*(7), 3377–3405.

Chiappori, P.-A., & Donni, O. (2009). *Non-unitary models of household behavior: A survey of the literature* (Tech. Rep.). IZA Discussion Papers.

Chile, G. o. (2013). *Chile en el panorama educacional internacional.*

Conti, G., & Heckman, J. J. (2012). The economics of child well-being. *NBER Working Paper*, *18466*.

Creal, D. (2012). A survey of sequential monte carlo methods for economics and finance. *Econometric Reviews*, *31*(3), 245–296.

Cunha, F., & Heckman, J. J. (2008). Formulating, identifying and estimating the technology of cognitive and noncognitive skill formation. *Journal of Human Resources*, *43*(4), 738–782.

Cunha, F., Heckman, J. J., & Schennach, S. M. (2010). Estimating the technology of cognitive and noncognitive skill formation. *Econometrica*, *78*(3), 883–931.

Del Boca, D., Flinn, C., & Wiswall, M. (2014). Household choices and child development. *The Review of Economic Studies*, *81*(1), 137–185.

Del Boca, D., Flinn, C. J., & Wiswall, M. (2016). Transfers to households with children and child development. *Economic Journal*, *Forthcoming*.

Doepke, M., & Tertilt, M. (2014). *Does female empowerment promote economic development?* (Tech. Rep.). National Bureau of Economic Research.

Duflo, E. (2000). Grandmothers and grandaughters: the effects of old age pension on child health in south africa.

Duncan, G. J., & Magnuson, K. (2013). Investing in preschool programs. *The Journal of Economic Perspectives*, *27*(2), 109–132.

Dussaillant, F. (2016). Usage of child care and education centers. *SAGE Open*, *6*(2).

Fiorini, M., & Keane, M. P. (2014). How the allocation of children's time affects cognitive and noncognitive development. *Journal of Labor Economics*, *32*(4), 787–836.

Fiszbein, A., Schady, N. R., & Ferreira, F. H. (2009). *Conditional cash transfers: reducing present and future poverty*. World Bank Publications.

Francesconi, M., & Heckman, J. (2016). Symposium on child development and parental investment: Introduction. *IZA DP*, *9977*.

Gayle, G.-L., Golan, L., & Soytas, M. A. (2015). What accounts for the racial gap in time allocation and intergenerational transmission of human capital?

Haddad, L., Hoddinott, J., Alderman, H., et al. (1997). *Intrahousehold resource allocation in developing countries: models, methods, and policy.* Johns Hopkins University Press.

Heckman, J., & Mosso, S. (2014). The economics of human development and social mobility. *Annual Review of Economics*, *6*, 689-733.

Heckman, J. J., Stixrud, J., & Urzua, S. (2006). The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. *Journal of Labor Economics*,

24(3), 411-482.

Keane, M., Todd, P., & Wolpin, K. (2011). The structural estimation of behavioral models: Discrete choice dynamic programming methods and applications. *Handbook of Labor Economics*, *4a*(331-461).

Klaas, M., Briers, M., De Freitas, N., Doucet, A., Maskell, S., & Lang, D. (2006). Fast particle smoothing: If i had a million particles. In *Proceedings of the 23rd international conference on machine learning* (pp. 481–488).

Macours, K., Schady, N., & Vakis, R. (2012). Cash transfers, behavioral changes, and cognitive development in early childhood: evidence from a randomized experiment. *American Economic Journal: Applied Economics*, *4*(2), 247–273.

Matzkin, R. L. (2007). Nonparametric identification. *Handbook of Econometrics*, *6*, 5307–5368.

Murphy, K. P. (2012). *Machine learning: a probabilistic perspective*. MIT press.

Nelson, C. A., & Sheridan, M. A. (2011). Lessons from neuroscience research for understanding causal links between family and neighborhood characteristics and educational outcomes. *Whither opportunity*, 27–46.

Paxson, C., & Schady, N. (2010). Does money matter? the effects of cash transfers on child development in rural ecuador. *Economic development and cultural change*, *59*(1), 187–229.

Roberts, B. W., Kuncel, N. R., Shiner, R., Caspi, A., & Goldberg, L. R. (2007). The power of personality: The comparative validity of personality traits, socioeconomic status, and cognitive ability for predicting important life outcomes. *Perspectives on Psychological Science*, *2*(4), 313–345.

Schady, N., Behrman, J., Araujo, M. C., Azuero, R., Bernal, R., Bravo, D., ... others (2015). Wealth gradients in early childhood cognitive development in five Latin American countries. *Journal of Human Resources*, *50*(2), 446–463.

Schennach, S. (2004). Estimation of nonlinear models with measurement error. *Econometrica*, *72*(1), 33-75.

Schoellman, T. (2014). Early childhood human capital and development. *American Economic Journal: Macroeconomics*.

Sørensen, H. T., Sabroe, S., Rothman, K. J., Gillman, M., Steffensen, F. H., Fischer, P., & Serensen, T. I. (1999). Birth weight and length as predictors for adult height. *American Journal of Epidemiology*, *149*(8), 726–729.

Thomas, D. (1994). Like father, like son; like mother, like daughter: Parental resources and

child height. *Journal of human resources*, 950–988.

Thomas, D., Contreras, D., & Frankenberg, E. (2002). Distribution of power within the household and child health. *Santa Monica: RAND. Mimeo*.

Todd, P. E., & Wolpin, K. I. (2007). The production of cognitive achievement in children: Home, school, and racial test score gaps. *Journal of Human capital*, *1*(1), 91–136.

11 Appendix

11.1 Identification of Measurement System

The measurement system is described by:

$$Z = \iota_0 + \iota_1 K + \boldsymbol{\varepsilon} \tag{61}$$

We normalize $E[k] = 0$ for every factor. The variance-covariance matrix of the measurement system is given by:

$$\Sigma_Z = \iota_1 \Sigma_K \iota_1' + \Sigma_\varepsilon \tag{62}$$

The matrix of moments Σ_Z contains $M(M+1)/2$ moments in order to identify the necessary parameters of the models. M is the total number of measures available and is equal to the sum of measures for each factor:

$$M = \sum_{k \in K} N_k = 151 \tag{63}$$

as we have

$$\begin{aligned}
N_{ln(S_0)} &= 23 \\
N_{ln(S_1)} &= 11 \\
N_{ln(S_2)} &= 13 \\
N_{ln(PG)} &= 8 \\
N_{\mu} &= 19 \\
N_{ln(I_1)} &= 8 \\
N_{ln(I_2)} &= 21 \\
N_{ln(\hat{e}_1^f)} &= 10 \\
N_{ln(\hat{e}_2^f)} &= 14 \\
N_{ln(\hat{e}_1^m)} &= 10 \\
N_{ln(\hat{e}_2^m)} &= 14
\end{aligned}$$

The dedicated factor structure assumed imposes that each measure loads exclusively to one factor. This implies that rather than $11 \times M$ factor loadings to obtain we only have to estimate M elements in ι_1 to be estimated. Given that the scale of the factor is irrelevant for the analysis, we can normalize one factor loading for each factor to be 1. In total, we have $M - 11 = 140$ factor loadings to be estimated.

The matrix Σ_K contains $(11 \times (11 + 1)/2)$ covariances to be estimated and Σ_ε has $M \times (M + 1)/2$. We see that it is necessary to make some assumptions about the correlation structure of the factors or of the measurement error system in order to be able to identify the system. If we assume that the measurement error in the system for skills at birth is independent of measurement error in the remaining systems $\varepsilon_m^{\ln(s_0)} \perp\!\!\!\perp \varepsilon_m'^k$ for $m = 1...N_{ln(s_0)}$, $k \in K, k \neq \ln(s_0)$, $m' = 1...N_k$ we have enough moments to identify the system. By doing this assumption, we are assuming that the elements in Σ_ε that correspond corresponding to $ln(s_0)$ and other factors are zero. With this, we have enough moments to identify the system.

11.2 Estimation

In this section I will derive the full likelihood function of the model as well as the filtering procedure to estimate it.

11.2.1 Likelihood function

The likelihood of the model is:

$$\mathcal{L}(\Theta|O;X) = P(O|X;\Theta) = P(O_1, O_2, O_3|X;\Theta)$$

$$p_0(O_0|\Theta, X)p_1(O_1|O_0, \Theta, X)p_2(O_2|O_1, \Theta, X) \tag{64}$$

Now, inspecting every element. The first term is composed by the observed outcomes in period zero. Given that the only one observed in this case is the first period of skills, this is composed then by that.

$$p_0(O_0|\Theta, X) = \int p_0(O_0, K_0|\Theta, X)dK_0 =$$

$$\int p_0(O_0|K_0, \Theta, X)p(K_0|\Theta, X)dK_0 =$$

$$E_{p(K_0|\Theta,X)}\left[P_0(O_0|K_0, \Theta, X)\right] \approx$$

$$\sum_{rr=1}^{RR} P_0(O_0|K_0^{\{rr\}}, \Theta, X) \tag{65}$$

for RR large, and for the $\{K_0^{\{rr\}}\}_{rr=1}^{RR}$ being drawn from the distribution $p(K_0|\Theta, X)$. K_0 is the set of unobserved factors relevant for period zero given by

$$K_0 = \{\ln(s_0), \ln(PG)\} \tag{66}$$

Note that in the model the distribution $p(K_0|\Theta, X)$ is not specified. I will assume that both factors are independent and each follow a normal distribution with mean zero and variance $\sigma_{s_0}^2$ and σ_{PG}^2 respectively. This way, evaluating the likelihood for period 0 ends

up being a process of drawing shocks from the distribution $p(K_0|\Theta, X)$, computing the likelihood of each shock given by the measurement system of the unobserved latent factors and averaging such likelihoods over the RR shocks.

For the first period the set of relevant factors is given by:

$$K_1 = \{\ln(s_1), \ln(e_1^{f,*}), \ln(\hat{e}_1^{m,*}), \ln(I_1^*), \mu_1\} \tag{67}$$

and the likelihood can be expressed as:

$$p_1(O_1|O_0, \Theta, X) = \int p_1(O_1, K_1|O_0, \Theta, X)dK_1 =$$

$$\int\int p_1(O_1, K_1, K_0|O_0, \Theta, X)dK_1dK_0 =$$

$$\int\int p_1(O_1|K_1, K_0, O_0, \Theta, X)p(K_1|O_0, K_0, \Theta, X)p(K_0|O_0, \Theta, X)dK_1dK_0 \tag{68}$$

Note that

$$p(K_1|O_0, K_0, \Theta, X) = p(K_1|K_0, \theta, X) \tag{69}$$

as O_0 would not carry more information beyond that in K_0 that is relevant for K_1. Also, note that

$$p_1(O_1|K_1, K_0, O_0, \Theta, X) = p_1(O_1|K_1, \Theta, X) \tag{70}$$

Taking into account the facts presented in Equations 69 and 70 we can express 68 as:

$$\int\int p_1(O_1|K_1, \Theta, X)p(K_1|K_0, \Theta, X)p(K_0|O_0, \Theta, X)dK_1dK_0 =$$

$$\int p(K_0|O_0, \Theta, X)\left[\int p(O_1|K_1, \Theta, X)p(K_1|K_0, \Theta, X)dK_1\right]dK_0 =$$

$$E_{p(K_0|O_0,\Theta,X)}\left[\int p(O_1|K_1, \Theta, X)p(K_1|K_0, \Theta, X)dK_1\right] = \tag{71}$$

in Equation 71 $p(O_1|K_1, \Theta, X)$ is given by the measurement system of factors, the likelihood of wages (for those that are observed) and the preference shocks cdf. We can re-write such expression as:

$$p(O_1|K_1, \Theta, X) =$$

$$p(\mathcal{Z}_1|K_1, \Theta, X) \times p(w^f|K_1, \Theta, X)^{(1-h^{f,*})} \times p(w^m|K_1, \Theta, X)^{1-h^{m,*}}$$

$$\times p(h^{f,*}, h^{m,*}, a|w^f, w^m, K_1, \Theta, X) \tag{72}$$

As specified previously, $p(\mathcal{Z}_1|K_1, \Theta, X)$ is given by the measurement system. $p(w^f|K_1, \Theta, X)$ is given by the measurement error associated to the observed wages:

$$\ln\left(w^j\right) = \beta_0^j + \beta_1^j yrschool^j + \beta_2^j Age^j + \beta_3^j (Age^j)^2 + \varepsilon_{w^j} \tag{73}$$

where ε_{w^j} is measurement error following a distribution $\varepsilon_{w^j} \sim N(0, \sigma_{\varepsilon^j})$.
Finally, $p(h_f^*, h_m^*, a^*|w^f, w^m, K_1, \Theta, X)$ is given by the probability of having the observed decisions as the optimal ones:

$$p(h_f^*, h_m^*, a^*|w^f, w^m, K_1, \Theta, X) =$$

$$p_{(\boldsymbol{\varepsilon_d^f}, \boldsymbol{\varepsilon_d^m})}\left(W(u^f(h^{f*}, h^{m,*}, a^*), u^m(h^{f,*}, h^{m,*}, a^*)) \in \arg\max_{\{h^f, h^m, a\}} W(u^f(h^f, h^m, a), u^m(h^f, h^m, a))|K_1, \Theta, X\right) \tag{74}$$

where $p_{(\boldsymbol{\varepsilon_d^f}, \boldsymbol{\varepsilon_d^m})}$ is the distribution of the preference shocks $\boldsymbol{\varepsilon_d^f}, \boldsymbol{\varepsilon_d^m}$.

$p(K_1|K_0, \Theta, X)$ is given by the transition equation. Note, however, that the dynamics of the system are only given through the skills of the child, the remaining factors do not have any dynamics carried from the previous period. This implies that such expression will be given by the skills production function and the distribution of heterogeneity in the

remaining factors. Being explicit:

$$p(K_1|K_0,\Theta,X) = p(\ln(s_1),\ln(e_1^{f,*}),\ln(\hat{e}_1^{m,*}),\ln(\hat{I}_1^*),\mu_1|\ln(PG),\ln(s_0),\Theta,X)$$

$$\int p(\ln(s_1),\ln(e_1^{f,*}),\ln(e_1^{m,*}),\ln(I_1^*),\mu_1|\ln(PG),\ln(s_0),\Theta,X) =$$

$$p(\ln(s_1)|\ln(e_1^{f,*}),\ln(e_1^{m,*}),\ln(I_1^*),\mu_1,\ln(PG),\ln(s_0),\Theta,X) \tag{75}$$

$$\times\, p(\ln(e_1^{f,*})|\mu_1\Theta,X) \tag{76}$$

$$\times\, p(\ln(e_1^{m,*})|\mu_1,\Theta,X) \tag{77}$$

$$\times\, p(\ln(I_1^*)|\mu_1,\Theta,X) \tag{78}$$

$$\times\, p(\mu_1|\Theta,X) \tag{79}$$

The term 75 is given by the production of skills and the remaining 76-78 are given by the distribution of heterogeneity in each factor: η_{e^f}, η_{e^m} and η_I. The term 79 is given by the distribution of heterogeneity in 14. Note that we can also use Monte-Carlo techniques to approximate the expression in 71 by:

$$\sum_{rr=1}^{RR} \hat{w}_0^{\{rr\}} \left[\int p(O_1|K_1,\Theta,X) p(K_1|K_0^{\{rr\}},\Theta,X) dK_1 \right] \tag{80}$$

where $\{K_0^{\{rr\}}\}_{rr=1}^{RR}$ are drawn from an importance distribution $g_0(K_0|\mathcal{Z}_0,\Theta,X)$ and the weights are given by:

$$\hat{w}_0^{rr} = \frac{w_0^{rr}}{\sum_{rr=1}^{RR} w_0^{rr}} \tag{81}$$

and the individual weights are defined:

$$w_0^{rr} \propto \frac{p(K_0|O_0,\Theta,X)}{g_0(K_0|\mathcal{Z}_0,\theta_0,\Theta,X)} \tag{82}$$

Note that after some algebra, we can define:

$$\tilde{w}_1 = \frac{p(O_1|K_1, \Theta, X)p(K_1|K_0, \Theta, X)}{g_t(K_0|, O_0, O_1, \Theta, X)} \tag{83}$$

where $g_t(K_0|, O_0, O_1, \Theta, X)$ is the proposal -importance- distribution from which the particles are going to be drawn. We will explain below what this distribution is. Note that replacing 83 into 71 we obtain:

$$\sum_{rr=1}^{RR} \hat{w}_0^{\{rr\}} \left[\int p(O_1|K_1, \Theta, X)p(K_1|K_0^{\{rr\}}, \Theta, X)dK_1 \right] =$$

$$\sum_{rr=1}^{RR} \hat{w}_0^{\{rr\}} \left[\sum_{rr'=1}^{RR} \tilde{w}_1^{rr'}(rr) \right] \tag{84}$$

And finally note that the dependence given between rr and rr' generates a $dirac$ measure in dependence (all that follow from rr different in the dependence path go to zero in rr'). Then, we can write the expression of the likelihood in the first period as:

$$p_1(O_1|K_1, K_0, O_0, \Theta, X) = \sum_{rr=1}^{RR} \hat{w}_0^{rr} \tilde{w}_1^{rr} \tag{85}$$

The computation of the likelihood for the second period is identical to that of the first period with the exception that we need to change the measurement system for the corresponding measures available in the second period and the childcare decision is not available in the behavioral model.

In this case we will use as importance distribution the same transition equation. The literature refers to this type of filtering as the bootstrap filter Creal (2012).

11.3 Filtering

Now that we have an expression for the likelihood function in a way that can be computed via simulation, I will present the algorithm used to evaluate the likelihood function at a given point:

Filtering Algorithm

1. Set t=0.
   (a) For rr=1....RR:
      i. draw $K_0^{\{rr\}}$ from proposal distribution $g(K_0|\Theta, X)$
      ii. Compute the weights $\hat{w}_0^{\{rr\}} = \frac{1}{RR}$
   (b) Compute likelihood for measurement system in $t = 0$: $\frac{1}{RR}\sum_{rr=1}^{RR} P_0(O_0|K_0^{\{rr\}}, \Theta, X)$
2. Set t=t+1
   (a) For rr=1....RR:
      i. Draw θ_t from proposal distribution (transition equation): $p(K_t^{\{rr\}}|K_{t-1}^{\{rr\}}, \Theta, X)$
      ii. Compute the weights $\tilde{w}_t^{\{rr\}} = p(O_t|K_t^{\{rr\}}, \Theta, X)$
      iii. Define $w_t^{\{rr\}} = \hat{w}_{t-1}^{\{rr\}}\tilde{w}_t^{\{rr\}}$
   (b) For rr=1...RR
      i. Define $\hat{w}_t^{\{rr\}} = \frac{w_t^{\{rr\}}}{\sum_{rr=1}^{RR} w_t^{rr}}$
   (c) Compute the likelihood for period t: $\sum_{rr=1}^{RR} \tilde{w}_t^{rr}\hat{w}_{t-1}^{rr}$
   (d) For rr=1....RR
      i. Re-sample RR particles $\theta_t^{\{rr\}}$ from step $(2.i)$ with probabilities $\hat{w}_t^{\{rr\}}$
      ii. Set $w_t^{rr} = \frac{1}{RR}$

It is usually assumed that it is costly to sample from the original distribution $p(K_t|K_{t-1}, \psi, X)$. Such is not the case of this article and then as importance distribution we will use the transition system as the importance distribution. When such distribution is used, the algorithm implemented receives the name of the bootstrap filter.

Figure 13: Particle Filtering Algorithm

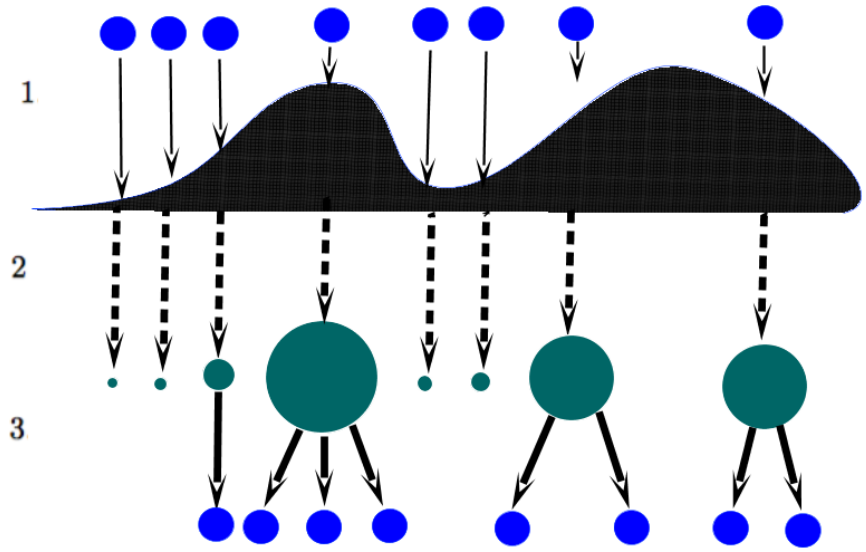


Figure 13 illustrates the particle filtering algorithm with eight particles. In the first step, particles are drawn from the proposal distribution $g(K_0|\Theta, X)$. In the second step, the likelihood of each particle is evaluated through the likelihood system $P_0\left(O_0|K_0, \Theta, X\right)$. In the third step, a new set of particles are drawn with the corresponding weight given by the measurement system. Some particles might die and some others are drawn multiple times.

11.4 Smoothing distribution

The smoothing distribution is useful if we are interested in making inference about the state of the unobserved factors. In this case, it is particularly interesting to make inference about the skills of children. The following procedure describes how to use the information provided in the model and in the data in order to derive the smoothing distribution of the unobserved latent factors. This procedure is adapted from Klaas et al. (2006):

I will use as main input for this file the article "Fast Particle Smoothing: If I had a Million Particles". I translate the notation in the one used in the paper. Define $O_{0:t} = \{O_0, O_1..., O_t\}$. The smoothed density is:

$$p(K_t|O_{0:2}) \tag{86}$$

where we basically condition on all the measures we have. Note that we can write Equation 86 as:

$$p(K_t|O_{0:2}) = p(K_t|O_{0:t}) \int \left(\frac{p(K_{t+1}|O_{0:2})p(K_{t+1}|\theta_t)}{\int p(K_{t+1}|\theta_t)p(K_1|O_{0:t})dK_t} \right) dK_{t+1} \tag{87}$$

And then we can approximate this distribution by $\hat{p}(\theta_t|O_{0:2})$ with:

$$\hat{p}(K_t|O_{0:2}) = \sum_{rr=1}^{RR} w_{t|T}^{(rr)} \delta_{K_t^{(rr)}}(K_t) \tag{88}$$

where $\delta_{K_t^{(rr)}}(K_t)$ is the Dirac distribution and

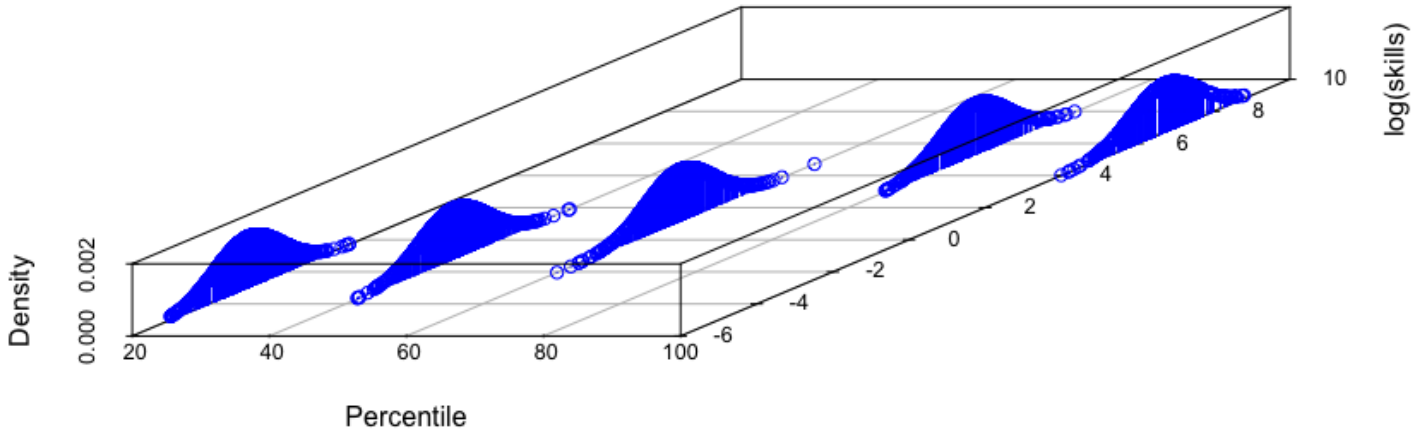
$$w_{t|T}^{(mm)} = w_t^{(mm)} \left[\sum_{rr=1}^{RR} w_{t+1|T}^{(rr)} \left(\frac{p\left(K_{t+1}^{(rr)}|K_t^{(mm)}\right)}{\sum_{kk=1}^{KK} w_t^{(kk)} p\left(K_{t+1}^{(rr)}|K_t^{(kk)}\right)} \right) \right] \tag{89}$$

where $w_{T|T} = w_T$

Smoothing algorithm

1. For t=0,1,2 perform the particle filtering to obtain $\{K_t^{rr}, w_t^{rr}\}_{rr=1}^{RR}$
2. Set $w_{2|2}^{rr} = w_2^{rr}$ for $rr = 1...RR$
3. For t=1,0 define $w_{t|2}^{(mm)} = w_t^{(mm)} \left[\sum_{rr=1}^{RR} w_{t+1|2}^{(rr)} \left(\frac{p\left(x_{t+1}^{(rr)} | x_t^{(mm)}\right)}{\sum_{kk=1}^{KK} w_t^{(kk)} p\left(x_{t+1}^{(rr)} | x_t^{(kk)}\right)} \right) \right]$

Figure 14: Smoothing Distribution of Skills According to Household's Income Percentile



The distribution of $log(skills)$ is plotted for representative households. Households located in the 20th, 40th, 60th, 80th and 100th percentile of total household income. The smoothed distribution of all the households is presented in Figure 11

11.5 Signal to Noise Ratio

Figure 15: Signal to noise ratio. Mother's effort (2012)

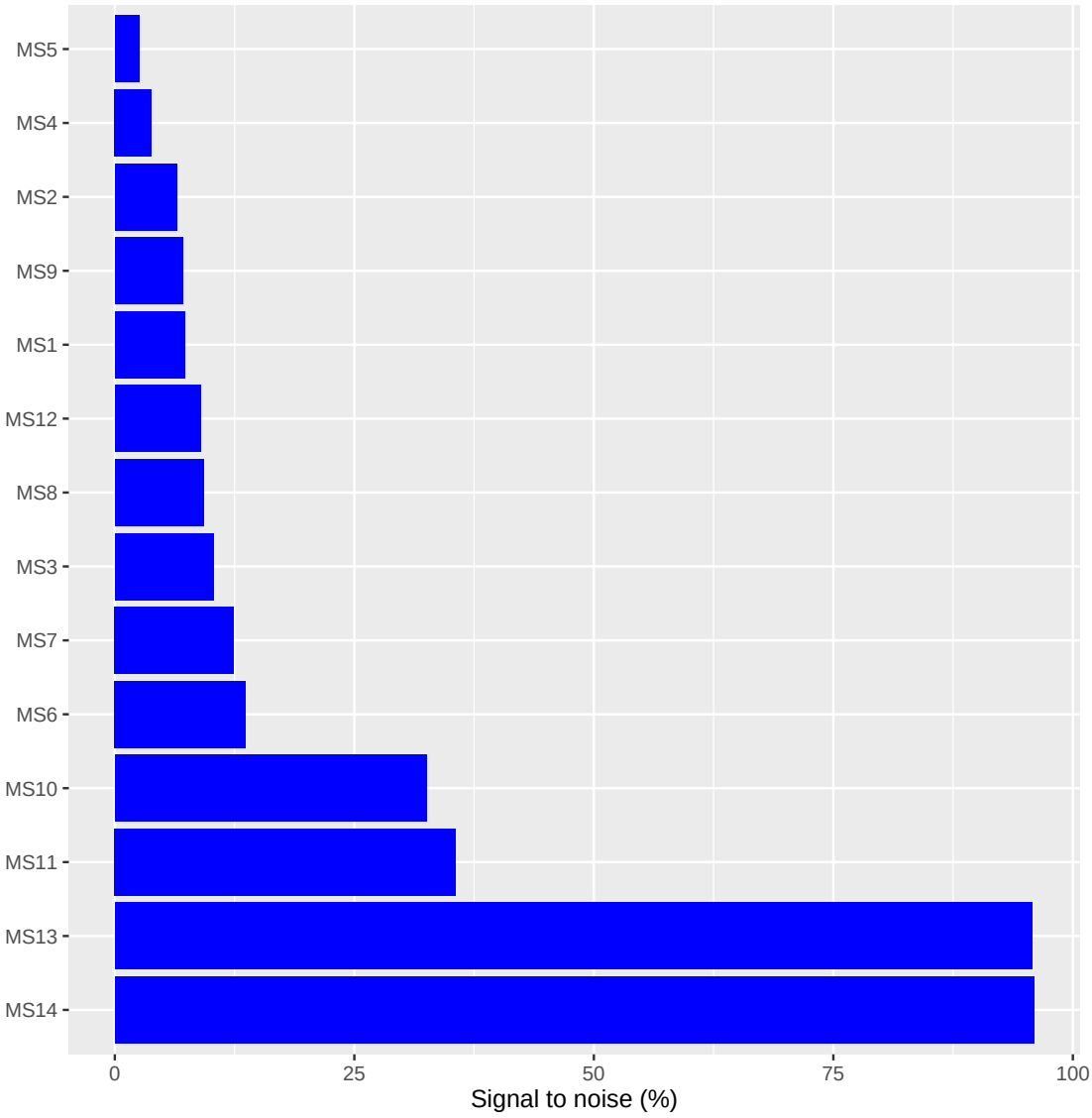
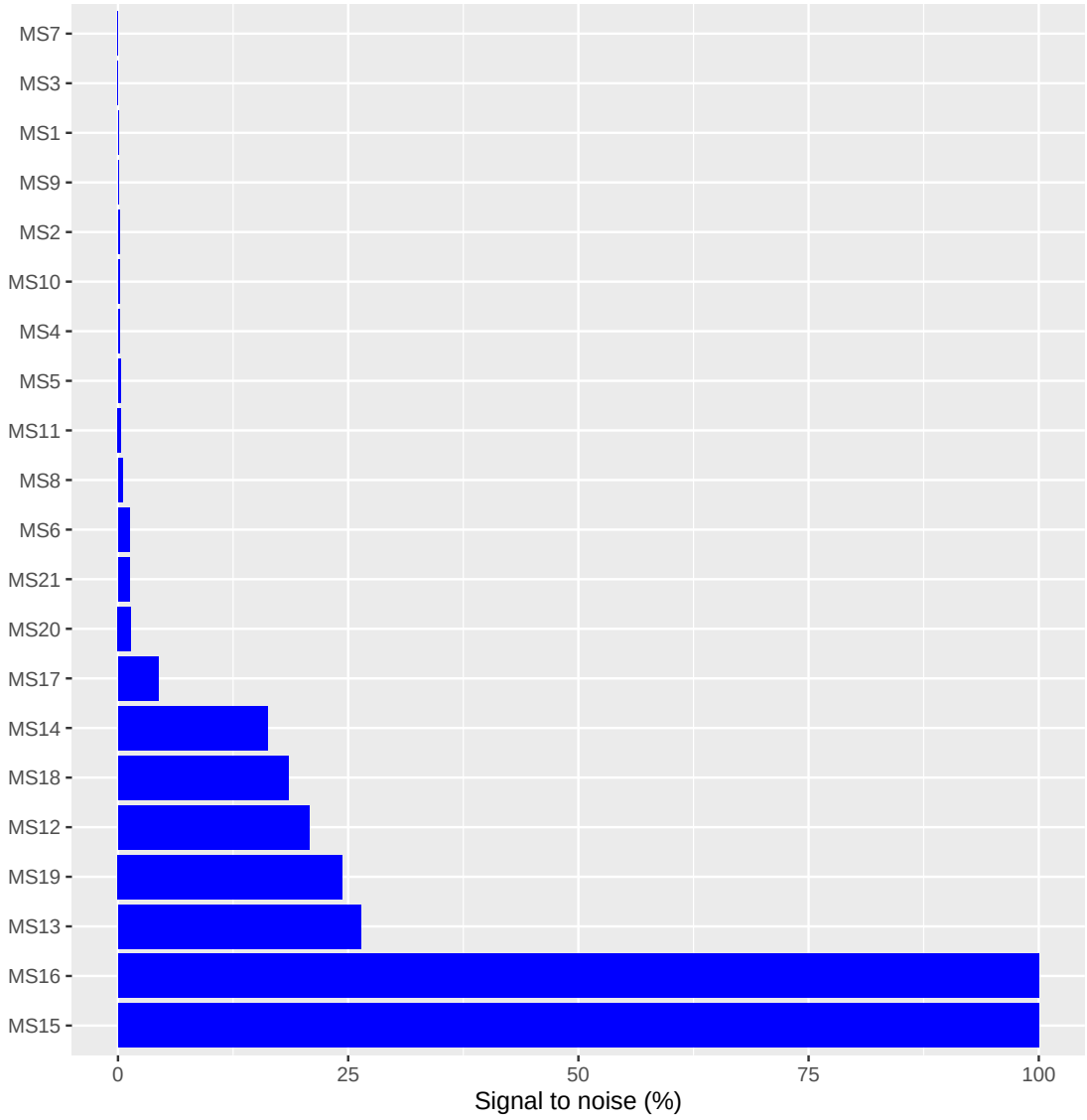


Figure 16: Signal to noise ratio. Monetary Investment (2012)



11.6 Cash Transfer Programs in Chile

The basic program through which poor families receive cash transfers from the central government is the "Unique Family Subsidy"[19]. Such program established a monthly transfer

[19]Subsidio Unico familiar in Spanish.

of $14,340 CLP in 2012, for a family in conditions of vulnerability[20] with one child[21]. The recipient of the transfer is always set to be the mother of the children who generate the transfer. In addition to be within the 40% most vulnerable, in order for the mother should be economically inactive in order to receive the transfer. However, the alternate program "Family Assignment" cash transfers of the same value for those mothers who were working, with a fadeout scheme [22].

In 2016, the basic amount of a transfer in the programs "Unique Family subsidy" and "Family Assignments" corresponded to $10,577. When compared to the $7,170 CLP of 2012, this represents an increase of 29% in real terms. Additionally, in 2014 the government of Michelle Bachelet implemented the implemented the "Permanent Family Contribution Program". In 2016, those families who were eligible to either "Unique Family Subsidy" or "Family Assignments" were automatically eligible to be part of the "Permanent Family Contribution Program". which consisted in a transfer of $43,042 anually for each children and one for the family as a whole. Thus, a family one child would be eligible to receive $86,084 CLP.

Overall, a family of one child that was receiving transfers from the "Unique Family Subsidy" program in 2012, would see an increase in the monetary transfers from the central government equivalent to 72.8% in real terms.

[20]The condition of vulnerability corresponds to a score below 11.734 in the "Ficha de ProtecciÛn Social". Approximately 40% of Chilean families lie below this threshold

[21]The $14,340 CLP were generated by the mother and the child, each generating a transfer of $7,170 CLP.

[22]The transfer scheme consisted of $7,179CLP for women with monthly wages below $187,515 CLP; $5,054 CLP for women whose wages was in between $187,515 CLP and $307,863 CLP; and $1,600 CLP for women whose wages was between $307,863 CLP and $480,163.