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

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Abstract

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

1 Introduction

Research in medicine, psychology and economics shows that skills shaped during the first years of life have 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. The results of these studies allow a better understanding of the key inputs that promote skills in young children.[2] For instance, they showed that parenting and general family environment are among the most relevant inputs in the production of skills (J. Heckman & Mosso, 2014; Schoellman, 2014).

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

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

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

for five Latin American countries, using a vocabulary test for children younger than five. Research in neuroscience shows that malleability of skills decreases with age (Nelson & Sheridan, 2011). 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 paper is to evaluate the effects that early childhood policy interventions have on the skill gaps between rich and poor children. Knowledge of the skill production function 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. Family investments in children might react to policy interventions. To analyze how early childhood policies affect resources allocated to children and skill formation, 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 paper makes several 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 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.

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, Mexico, Nicaragua and Colombia (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 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% (U. Chile, 2010).

A limitation of cash transfers is that it is not possible 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 in-kind 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

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

amount of resources that governments spend on enriching childhood environments, and given the fact that events during childhood heavily influence adult outcomes, it is important to understand the most cost-effective way of allocating these resources, whether through cash transfers or in-kind.

This paper also contributes to the literature of household decisions and child outcomes by allowing individual family members to have different preferences. 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 mothers 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 household members translates into different child outcomes.

The dataset used in this article allows me to overcome some empirical limitations that the literature has previously faced. For instance, studies have shown 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 parental skills 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.

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. 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 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. Additionally, households living in neighborhoods with a large number of preschool providers might live in a children friendly environment, where the availability of goods to increase skills in children is relatively high.

The survey used for this study is the Early Childhood Longitudinal Survey from Chile (ECLS). This survey was developed with the goal of precisely characterizing the skill formation process in children. Therefore, 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 and financial econometrics literature (Murphy, 2012; Creal, 2012), I propose a feasible computational approach for dealing with the high dimensionality integration 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 skill measures. Most of the prior research analyzing the child skill formation process uses data from the United States. By analyzing this process in the context of Chile, 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 poor children face significant disadvantages.

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, exclusively by 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 that all the bargaining power is explained by the consumption of a single good.

In this paper, I propose a new framework for estimating collective models of household behavior. I use information from questionnaires related to female empowerment and gender roles to assess the bargaining power of each household member. The use of answers to such questions, combined with exogenous variation in the distribution factors, allows me to identify the Pareto weight of each member in the household. Following such an identification strategy, I am also able to allow for unobserved heterogeneity.

The data from test scores show significant large gaps in skills between rich and poor children at age 5. The skill gap 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 by differences in parental skills and monetary investments. Additionally, , the model parameter estimates show 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. Given that women have lower bargaining power, they contribute more to the provision of public goods within the household. This particular mechanism explains 15% of the differences in time investments between mothers and fathers.

I use the estimated behavioral model to simulate the effects that cash transfer programs, free childcare subsidies, and in-kind transfers have on the skill gap between rich and poor children. Although less prevalent than the other two programs, in-kind transfers are currently being implemented in Chile through the "Chile Grows with You" program. 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. I summarize the main points of this paper in Section 8.

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 make relevant to the production of child skills, is that of labor supply. As household members increase their participation in the labor market, this will bring more monetary resources to the household but will reduce the amount of time parents interact with their children. For this reason, the impact of labor force participation on the skills of children is not obvious at first glance.

The question of how labor supply decisions affect the production of skills in young children has been 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 data limitations, she 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,Bernal (2008) finds that one year of full employment decreases the skills in children by approximately 0.13 of a standard deviation.

Del Boca et al. (2014) extend the results of Bernal (2008) and take into account that both parents participate 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 interaction with their children. Additionally, they incorporate decisions about how much money to allocate to monetary investments in children versus consumption. Results show that, when mothers increase time spent in the labor force, the potential negative effect is not only alleviated by the increase in the amount of resources due to wages but also by the fact that the father starts to spend more time with the children at home. One of the main conclusions is that time of both fathers and mothers are relatively more important than monetary investments in the production of child skills. Gayle et al. (2015) extends the modeling framework of Del Boca et al. (2014) to incorporate endogenous fertility. However, they do not observe test scores in their data or monetary investments by parents and ignore the role of preschool education.

The article that is most related to this paper is Del Boca et al. (2014). This paper extends Del Boca et al. (2014) in several ways. First, I incorporate the decision to enroll a child in preschool services. This is important given that subsidizing preschool is one of the most important policies to improve the conditions in which children develop, and to increase 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 important. First of all, in most developing countries, cash transfers to families with children are given to their mothers, motivated by the findings 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). To assess the effect that targeting individual household members has 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. 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 modeling household behavior using a collective approach, I am able to assess the extent to which empowering women translate into better child outcomes.

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

The dataset I use allows me to incorporate several facts about the skill formation process in children that were not incorporated in Del Boca et al. (2014). First of all, there is a consensus in the literature that skills are multiple (emotional, physical, cognitive). In this paper, 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. Additionally, an important element in the skill formation process is their dependence on parental skills (Francesconi & Heckman, 2016). Ignoring parental skills when estimating a production function 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.

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 (Cunha et al., 2010). 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 skill production function (Cunha et al., 2010; Cunha & Heckman, 2008; J. J. Heckman, Stixrud, & Urzua, 2006). This paper is the first to estimate the production function of skills via a latent-factor approach, nested within a collective model of household behavior.

The second area of related literature the empirical implementation of collective models of household behavior. The income pooling assumption establishes that, in a household composed of various members, it does not make a difference if transfers are given to one member or the other. Ultimately, what matters is the overall resources of the household. This 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). The rejection of this assumption has motivated a significant amount of research aimed at exploring alternatives. The collective model of household behavior assumes that each parent has his/her own preferences and that the decision reached in the household is Pareto efficient (Chiappori & Donni, 2009). The collective approach has resulted in better empirical predictions than the unitary framework.

Although there is an extensive literature exploring the properties of the collective model of household behavior, there are still very few empirical implementations of the 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 spending time with their children. They do not model how the time parents spend on their children impacts child skills. In this paper, I asume parents spend time with their children in part to augment their skill set.

Additionally, this paper 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 about 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 ignore the fact that every good consumed within the household has a public component. For example, it is also possible that couples care about each other's clothing. In this paper, rather than using private goods, I use answers provided from questionnaires about female empowerment and gender roles as noisy measures of the bargaining power within the household.

This article also contributes to the literature on optimal design of policies for 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. In some cases, such as in Brazil and Mexico, this program accounts for the largest social assistance program executed by the central government (Fiszbein et al., 2009). In most countries, the design of such programs establishes that, in households with children, the mother of the child receives the monetary transfers. This is supported by findings such as those 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 to women translate into better child outcomes than those made to men. The common interpretation of this fact is that women's preferences are more aligned with child outcomes and, therefore, making transfers to them is more efficient. However, to establish the mechanism that is generating such an outcome, it is necessary to estimate an economic model able to identify all possible channels.

The finding that transfers made to women result in better child outcomes deserves additional analysis. One interpretation is that women spend their own income on public goods, as explained by Bobonis (2009), or that they have stronger preferences for child outcomes than men. However, 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. Having women with stronger preferences for child outcomes is not a necessary condition. 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, because, as women become relatively more powerful, they can devote resources derived from child labor into their own private consumption. It is important for the design of policies to identify and explain the mechanism generating the positive relationship between women's empowerment and child outcomes. In this paper, I allow parents to have different preferences for children. By estimating the structural parameters of the model, I can analyze which mechanisms generate such a relationship.

Finally, this paper is related to the literature exploring the production of skills in children. Todd and Wolpin (2007) present alternative ways of estimating the production function 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 the joint condition of multiple skills and that the productivity of inputs might vary with age. As both inputs and outputs are observed with error, the authors estimate the 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. For the econometric implementation, I use a latent factor structure as in Cunha et al. (2010). However, to account for the endogeneity of inputs, I use an economic model of household behavior. Although Cunha et al. (2010) is considered a seminal contribution to the skill production function literature, there is little scope for counterfactual analysis because the inputs are hard to interpret. The measures of investments do not map to any possible effort levels or monetary investment in the family. In this paper, by embedding the skill production function within model of household behaviors, counterfactual analysis can be performed with easy interpretation of findings.

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. I use a unique dataset from Chile. 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

I 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 good economic performance during the last twenty years.[4] Two of the most distinctive facts about the Chilean economy are its 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 countries that are similar 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 for 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. Not every test was answered by all the children, as all of them include different age specifications.[5] The description of the tests included in the sample is included in Tables 1 and 2. I use these test scores as noisy information about children's skills

Given that I want to identify how families make decisions about 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 identify how parents reach such decisions in a context where there are multiple members with plausibly different preferences.

In the economic model, I consider the case of families with only one child under the age of five. For that reason, I 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-year age range.[6] The reason for doing this is that allowing

[4]Since 2012, Chile has been considered as a developed country for the World Bank. However, most of the literature treats it as a developing country, especially 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 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) and in the main analysis of Del Boca et al. (2014).

for multiple children in the economic model would imply solving additional questions that are not the main goal of this paper. For instance, I would need to identify or take a stance on whether parents have the same preferences for boys and girls, or whether they have preferences for equality of skills among children, as opposed to devoting more resources to the most promising child. Moreover, we also would need to understand to what extent there is a quality-quantity tradeoff in fertility decisions: do parents prefer to have more children and devote fewer resources to each of them or to terminate their childbearing early and devote most resources to a limited number of children.

In Table 3, I report the summary statistics of families in the survey. We see that fathers, whose average age is 35, are on average four years older than mothers, whose average age is 31. 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 44 hours a week, which is more than twice the average of mothers, at 18 hours. As will be discussed in the preliminary evidence section, unemployment rates do not explain a great deal of the low level of hours that mothers participate in the labor market. This is 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 \$83,890 Chilean Pesos (CLP) whereas men make \$104,220 CLP.[7] In terms of ages of children, we see that they are on average 50 months old.

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 4 and 5. In Figure 3 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 are sharing a meal, talking to them and teaching them the numbers or letters. The least common activities are taking the children to cultural activities or parks or reading to them.

In Tables 6 and 7, I report all the subdomains of the test scores and parental assessments used for the skills of children in the two waves of the survey. As can be seen, in both waves I use information about test scores related to vocabulary tests and cognitive abilities, and also parental assessments related to overall child development, together with behavioral and emotional skills.

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 8.

To incorporate the fact that parental skills affect skills of children, I use scores of different tests performed to mothers of the children selected. In Table 9, I report all the test scores used, which include two widely-used test scores assessing general cognition (Wais Test Scores), together with the Big Five personality traits scores (BFI).

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

A relevant input into the production of skills is the amount of monetary investments that parents make in their children. This type of investment can include any type of materials that can improve the living conditions of children or that can stimulate their learning experiences, 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 in 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 assumptions. Going beyond previous studies, I 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 those 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 10 and 11.

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 manages 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 the extent to which the woman has a say in the household and whether she has any power when making decisions of economic relevance. The variables used to assess the degree of a woman's empowerment in the household are presented in Table 12. Tables 13 and 14 include summary statistics of the answers provided on 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 of extra time. However, as noted in Table 14, women also consider that they should be more in charge of children involved in the workforce. 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.

In addition to the ECLS, I use information about the location of every preschool provider in Chile and I compute the distance from each center to each household. I use the relative availability of preschool providers near each household as a shifter in the cost of childcare and monetary investments in children. In Figure 1, I report summary statistics about the availability of childcare providers for households. We see that, on average, the nearest preschool provider is 0.61 kilometers away from the household. Additionally, in Figure 2 I report an example of how the information about availability of preschool allows me to geographically locate each center.

Finally, I use information from the household survey (CASEN) in 2011, together with the CENSUS dataset in order to obtain some of the distribution factors. I use as distribution factors the share of non-labor income in the hands of men, the difference in ages between fathers and mothers, and the sex ratio in the city of residence, as well as the gender wage gap and the gender unemployment ratio in each region. The descriptive statistics of the distribution factors can be found in Table 15.

4 Preliminary Evidence

In this section, I 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 5. 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 old. This can be seen in Figure 6. The figure reports the scores in different tests and parental assessments. All of them are standardized to be mean zero and variance one. We see, for instance, that children in the lowest income quintile score 0.1 of a standard deviation below the mean on the Battelle test score for Motor Skills, whereas children in the richest quintile score 0.15 of a standard deviation 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 Mothers spend more time with children than do fathers

As shown previously in Figure 3, mothers spend more time with their children, in every activity, than fathers do. One possible explanation is the difference in labor supply. Fathers specialize in remunerated activities in the labor market, whereas mothers specialize in taking care of children. In Tables 16 and 17, I analyze the relationship between labor supply of both spouses and time spent with the child. 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 16 and 17.

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 by parents. For example, when one parent increases his/her labor supply, that parent decreases the amount of time spent with the child and thus the other parent might react by increasing the amount of time spent interacting with the child. This compensating behavior might diminish the plausible negative impact on child development of an increase in female labor force participation.

The evidence from these regressions is complemented with the estimates of regressions in differences reported in Table 18. The results again seem to suggest that, as members participate more in the labor market, they decrease the amount of time spent with their child, but this is compensated by an increase in the spouse's time with their child.

Although labor market behavior might explain part of the differences in the time investments between

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

mothers and fathers, there are other stories consistent with such a result. The differences might be due to preferences, as mothers find it less costly to invest time in their children, or due to differences in productivity, 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.

4.3 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 to the fact that women's 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. Table 19 presents 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 the IQ level of the primary caregiver, total household income, grades of schooling of both parents and their ages, we 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 20, some regressions of child investments and female empowerment are presented. I 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 manages the income are more likely to have toys for the development of children, and the frequency of consumption of fruits and vegetables is higher whereas that of bread is smaller. Similarly, households that are more accepting of the opinion that women should not work and should exclusively take care of their children are more likely to have the children sharing their bed with someone else, which might be an indicator of lower investments in children.

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 are either some unobservables that are not captured in the regressions, which are also correlated with female empowerment, and which positively affect 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, and skills of children, among other preferences, so that we can understand whether the relationship between female empowerment and child outcomes arises from such patterns or either due to unobserved heterogeneity.

4.4 Female Labor Force Participation

As mentioned before, mothers participate in the labor market 19 hours a week on average, whereas fathers do so 44 hours a week. One plausible explanation can be due to involuntary unemployment: it is harder for women to find a job offering a wage higher than their reservation wage, 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 with young children decide not to participate in the labor market. As can be seen in Figure 4, this is characteristic of women across all age groups. Most of them are not working or looking for a job and 83% of them state that the main reason is that 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 about 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 determined by the market.

5 Economic Model

In this section I, describe the economic model used to rationalize investments in children together 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 made only 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 whether or not the child attends preschool (a_t) and then a_t can take the value of zero or one depending on whether the child goes to preschool.

There is a preference shock $\boldsymbol{\epsilon_t}$ associated with each decision about labor supply and preschool. Because there are two decisions about labor supply and two possible decisions about preschool, 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

[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 resource allocation of the household.

is given by the following utility function:

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

$$\alpha_{5,t}^j h_t^j (1 - a_t) + \epsilon_{d,t}^j q_t^{j,d} \tag{1}$$

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 (PG), which are 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 ($\eta_{s,t}$). 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. This captures the idea that, by having additional household members, not only might the production of skills 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

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

[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 is not unreasonable.

The terms $\eta_{e_t^j}$ and η_{I_t} are unobserved heterogeneity. This term captures the fact that parents can differ in unobserved ways in how productive they are in terms of the time and monetary investments in their children. 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 $\eta_{s_t^j}$ reflect 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 start behaving more as agents making their own decisions, which might have consequences for 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.

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

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, which is the time constraint for each agent:

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

the non-negativity constraint:

$$c_2^f, c_2^m, I_2, e_2^f, e_2^m \geq 0 \tag{9}$$

and the budget constraint

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

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

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

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 and a can take the value of zero or one depending on whether or not the child goes to preschool.

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 $\bar{\mu}$ 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 in 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, which 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]

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

[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 necessary 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.

[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).

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 impact on the bargaining power. Descriptive statistics of these variables can be found in Table 15. 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 of the household.

The state variables are given by:

$$\Psi_t = \{r_t, s_{t-1}, \boldsymbol{\eta}, \boldsymbol{\epsilon_t}, \Xi_t, E_t, \{\epsilon^j_{d,t}, Y^j_t, w^j_t\}_{j=m,f}, P_a, P_I\} \tag{18}$$

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

$$\boldsymbol{\eta}_t = \{\eta_{I_t}, \eta_{e^f_t}, \eta_{e^m_t}, \eta_{\mu_t}, \eta_{s_t}\} \tag{19}$$

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. I solve this by first finding the optimal decisions about investment, consumption and effort, for each labor supply-childcare decision, and then choosing 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:

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

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

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

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

$$c_2^{m,*} = \max\{\frac{\alpha_{1,2}^f\mu_2 I_2}{\theta_1\kappa_2^2(\mu)}, \zeta\} \tag{24}$$

$$e_1^{m,*} = \frac{\left[\kappa_2^2(\mu_2)\theta_2 + \beta\kappa_2^2(\mu_2)\theta_2\theta_0\right]\gamma_1}{(1-\mu)\alpha_{4,2}^m(1+h_2^m)}\xi_1(m)\exp\left(-\eta_{e_1^m}\right) \tag{25}$$

$$e_1^{f,*} = \frac{\left[\kappa_1^2(\mu_1)\theta_2 + \beta\kappa_2^2(\mu_2)\theta_2\theta_0\right]\gamma_0}{\mu\alpha_{4,2}^f(1+h_2^f)}\xi_1(f)\exp\left(-\eta_{e_1^f}\right) \tag{26}$$

$$I_1^* = \frac{\left[\kappa_1^2(\mu_1)\theta_1 + \kappa_2^2(\mu_2)\theta_0\theta_1\beta\right]\left(h_2^f w_2^f + h_2^m w_2^m + Y_2^f + Y_2^m + \Xi - P_a a\right)}{\kappa_1^1(\mu_1) + \kappa_1^2(\mu_1)\theta_1 + \beta\theta_0\theta_1\kappa_2^1(\mu_2)}\exp\left(-\eta_{I_1}\right) \tag{27}$$

$$c_1^{f,*} = \max\{\frac{\alpha_{1,2}^f\mu_2 I_2}{\theta_1\kappa_1^2(\mu_1) + \beta\theta_0\theta_1\kappa_2^2(\mu_2)}, \zeta\} \tag{28}$$

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

where

$$\xi_t(j) = \frac{\left(\gamma_j \mu \alpha^f_{4,t}(1+h^f_t)\right)^{\frac{\phi}{1-\phi}}}{\gamma_0\left[\gamma_0(1-\mu)\alpha^m_{4,t}(1+h^m_t)\right]^{\frac{\phi}{1-\phi}} + \gamma_1\left[\gamma_1\mu\alpha^f_{4,t}(1+h^f_t)\right]^{\frac{\phi}{1-\phi}}} \tag{30}$$

$$\kappa^i_t(\mu) = \mu\alpha^f_{i,t} + (1-\mu)\alpha^m_{i,t} \tag{31}$$

$$\zeta = 1.0e-5 \tag{32}$$

and

$$\gamma_j = \begin{cases} \gamma_0 \text{ if } j = f \\ \gamma_1 \text{ if } j = m \end{cases} \tag{33}$$

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

$$\begin{aligned}(h^{f,*}_2, h^{m,*}_2) = \max_{\{h^f_2, h^m_2\}} & \mu_2 u^f_2(c^{f,*}_2(h^f_2, h^m_2), h^f_2, e^{f,*}_2(h^f_2, h^m_2), d^f_2(h^f_2, h^m_2), s_2(h^f_2, h^m_2)) + \\ & (1-\mu_2) u^m_2(c^m_2(h^f_2, h^m_2), h^m_2(h^f_2, h^m_2), e^{m,*}_2(h^f_2, h^m_2), d^m_2(h^f_2, h^m_2), s_2(h^f_2, h^m_2))\end{aligned} \tag{34}$$

$$\begin{aligned}(h^{f,*}_1, h^{m,*}_1, a) = \max_{\{h^f_1, h^m_1, a\}} & \mu_1 u^f_1(c^{f,*}_1(h^f_1, h^m_1, a), h^f_1, e^{f,*}_1(h^f_1, h^m_1, a)), d^f_1(h^f_1, h^m_1, a), s_1(h^f_1, h^m_1, a)) + \\ & (1-\mu_1) u^m_1 c^m_1(h^f_1, h^m_1, a), h^m_1(h^f_1, h^m_1, a), e^{m,*}_1(h^f_1, h^m_1, a), d^m_1(h^f_1, h^m_1, a), s_1(h^f_1, h^m_1, a)) \\ & + \beta\left[V_2(\Psi_2(h^f_1, h^m_1, a)\right]\end{aligned} \tag{35}$$

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:

$$K = \{\{\ln(s_t), \ln(e^{f,*}_t), \ln(e^{m,*}_t), \ln(I^*_t), \mu\}_{t=1,2}, \ln(PG), \ln(s_0)\} \tag{36}$$

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:

$$Z_m^k = \iota_{m,0}^k + \iota_{m,1}^k k + \varepsilon_m^k \text{ for } m = 1...N_k \tag{37}$$

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 4 - 11. 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:

$$P(O|X;\Theta) = \mathcal{L}\left(\Theta|O;X\right) \tag{38}$$

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 the 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 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:

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

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

$$\mathcal{Z}_2 = \{\ln(s_2), \ln(\hat{e}_2^f), \ln(\hat{e}_2^m), \ln(\hat{I}_2), \mu_2\} \tag{39}$$

Note that I have measures of μ_2 available only for the second period. The exogenous characteristics are given by the age, grades of schooling, age of parents and distribution factors in E_t.

Given that we need to integrate over the the distribution of the unobserved factors (because 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, because, 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 and the derivation of the likelihood function are described in Appendix 10.2.

For purposes of estimation, I assume that the preference shocks $\boldsymbol{\epsilon_t}$ are distributed according to a normal distribution with no correlation between choices. The unobserved heterogeneity terms, $\eta_{e_t^j}$ also follow 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 37. I assume they are distributed according to a normal distribution and that they are independent of each other but this is not an identifying assumption.

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-year 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 in Table 21. 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 22 and some details about the age distribution of the children included, for the 2012 wave, are included in Table 23. The preliminary evidence section uses all the information available in the survey. However, the results from the preliminary section also hold when using the sample used for the model. These results are available in the online appendix.

6.1 Identification

The identification argument is divided into three parts. First, I show how the parameters of the measurement system described in 37 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:

$$Z = \iota_0 + \iota_1 K + \boldsymbol{\varepsilon} \tag{40}$$

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 $\boldsymbol{\varepsilon} \in \mathbb{R}^M$ 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 ensure identification of the system. The first step is to normalize the first element of ι_1 for each measure to one, which corresponds to setting $\iota_{1,1}^k = 1$ for every factor $k \in K$ in Equation 37. The location normalization corresponds to setting the mean of each factor to a specified level. The arbitrary scale is set to be:

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

$$\mathbb{E}[\mu] = 0.5 \tag{41}$$

I also set normalizations for effort levels and investments, which 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, I can obtain the covariances by noting that:

$$\Sigma_Z = \iota_1 \Sigma_K \iota_1' + \Sigma_\varepsilon \tag{42}$$

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 10.1.

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

$$\frac{Cov(Z_m^k, Z_1^{\ln(s_0)})}{Cov(Z_1^k, Z_1^{\ln(s_0)})} = \iota_{m,1}^k \tag{43}$$

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

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

6.1.2 Distribution of latent factors

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

$$ME_j = \{\frac{Z_j^k}{\iota_{j,1}^k}\}_{k \in K} \tag{45}$$

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

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

$$\mathbb{E}\left[me_1 | K, me_2\right] = 0 \tag{47}$$

$$me_2 \perp\!\!\!\perp \theta \tag{48}$$

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:

$$p(K) = \frac{\int_{-\infty}^{\infty} e^{-i\chi K} e^{\left(\int_0^\chi \frac{E\left[iME_1 e^{i\psi ME_2}\right]}{\left[e^{i\psi ME_2}\right]} d\psi\right)} d\chi}{2\pi} \tag{49}$$

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

$$Cov(Z_m^l, Z_{m'}^{k'}) = \iota_{m,1}^k \iota_{m',1}^{k'} Cov(k, k') + Cov(\varepsilon_m^k, \varepsilon_{m'}^{k'}) \tag{50}$$

6.1.3 Technology of Skill Formation

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

$$p\left(\ln(s_{t+1}) | \ln(s_t), \ln(\tilde{e}_{t+1}^f), \ln(\tilde{e}_{t+1}^m), \ln(\tilde{I}_{t+1}), \mu, \ln(PG)\right) \tag{51}$$

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

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

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

where the expectation is taken with respect to the distribution in 51. 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 in which we are interested, we need to impose some restrictions. In particular, if we assume that the term η_{s_t} enters additively in 52, I can trivially identify the production of skills. Additionally, the distribution of η_s is identified as:

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

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

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

$$P\left(\eta_{s,t} \leq \tilde{s}_{t+1} - f_s\left(s_t,\tilde{e}_t^f,\tilde{e}_t^m,\tilde{I}_t^m\right)|\ln(s_t),\ln(\tilde{e}_t^f),\ln(\tilde{e}_t^m),\ln(\tilde{I}_t^m)\right) \tag{53}$$

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 of mothers and fathers. The main idea is that variation in such instruments will cause a movement along the Pareto frontier that is exclusively generated by the change in 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 these factors, and variation is given in a way that is exogenous to the household. In Table 15 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, I impose the exclusion restriction that differences in ages and schooling do not affect the behavior of 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 its 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. There are seven different programs giving monetary transfers to families in Chile, but the basic ones correspond 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 on 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 a lower score on the Social Protection Card are eligible for subsidies, all received by the mother, depending on their score, the months they have currently been beneficiaries of the programs and the demographic composition of the household.

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. Using variation in responses to the female empowerment and gender roles questionnaires, we can identify the extent to which non-labor income affects the process of decision-making within the household. The structure of the basic monetary transfers in Chile is reported in Figure 7. A description of how the monetary subsidies scheduling system has evolved over time is available in the Appendix in Section 10.5.

At this point, it is important to normalize 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:

$$\mathbb{E}\left[e_t^{f,*} \mid \mu = 0.5, h^f = 1\right] = 1 \tag{54}$$

$$\mathbb{E}\left[I_t^* \mid \mu = 0.5, d = 10\right] = 1 \tag{55}$$

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 allow me to identify the key parameters.

Because I see variation in effort levels in both, fathers and mothers, due to changes in distribution factors, this allow me to identify preferences for children of 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 allow me to identify the preferences for consumption of mothers and fathers.

[15] "Ficha de Proteccion social" in Spanish

Identification of the remaining parameters follows standard arguments in the literature. For 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 as long as we have variation in the number of preschool providers within five kilometers of households. In Figure 1, I show that there is 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, by 450%. Following the normalization in Equation 55, 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, together with the corresponding standard errors, are presented in Tables 24 - 30. As we see, childcare services tend to liberate more time resources for 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 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 because 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 skills 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 because 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 the man and woman decreases, the bargaining power of the man decreases as well. 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. With the estimation results I am able to extract the proportion of the variance due to true signal and the proportion due to noise.

$$\text{Signal-noise ratio}_{m,k} = \frac{\iota_{m,1}^2 Var(k)}{\iota_{m,1}^2 Var(k) + Var(\varepsilon_m^k)} \tag{56}$$

In Figures 14 - 15, I present the signal to noise ratio of the measurement system of the model for measures of effort and investments.[16] We find that cultural activities are the most informative about time investment in children, while 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 that such an activity is the one that is really productive, rather than performance of cultural activities itself. Making inferences about which activities are more productive requires more analysis.

7.1 Model fit

The model does a good job when predicting labor force participation and childcare decisions of the household. In Tables 33 and 34, 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 8, I 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 either the model or the data.

I report the predicted levels of childcare demand and how they compare with what is observed in the data in Table 35. The model does a good job at predicting the demand for childcare services according to female labor force participation. 67.7% of children living in families where the mother works attend preschool services, whereas the corresponding number for children living in families where the mother does not participate in the labor market is 42.9%. The corresponding proportions predicted in the model are 68.4% and 41.6%.

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 10 - 11. As we can see, in both cases the model fits the data well. Finally, the model does a good job at predicting the wages for men and women. In Figure 12, I report the estimated distribution of wages for women and men, both those predicted and those observed in the data. I report only the estimated wages for agents who participate in the labor market. The model does a good job of predicting not only the average wage but also the distribution.

With the information about measures and the information about the production of skills, we can get a more precise estimate of 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

[16] The signal to noise ratio of all the remaining measures for all the latent factors is available in the online appendix. The estimates of the factor loadings are also available in the online appendix.

each individual in the sample, is estimated and the results are reported in Figure 13. The details for the construction of the smoothing distribution are presented in Appendix 10.4. The results confirm huge disparities in skills between rich and poor kids.

7.2 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 the effects of such policies on 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 the 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. using the resources of the first policy counterfactual in order to perform in-kind transfers 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 is 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 has 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 among various policies are described in Appendix 10.5. Given that governments seem to increasingly spend 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 a 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 the extent to which this condition is justified, and to get an idea of whether it makes sense to spend additional resources in targeting an individual household member as the recipient of such transfers, in the second counterfactual I simulate what would happen if we set the father, rather than the mother, as the recipient of the transfers.

Free childcare and 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. Partly due to this policy, Chile is now the country with the highest expenditure on preschool education as a share of total government expenditure, among countries in the OECD. [17] 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. Although probably less prevalent than childcare subsidies or cash transfers, in-kind transfer programs are starting to become more popular in developing countries. In Chile, for example, such transfers are being done through the "Chile Crece Contigo"[18] (ChCC) program, established in 2009. ChCC is composed of 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 parents such as a 24-hour phone line for inquiries about child development, and the distribution of books, toys, songs and story books for children, as well as providing learning materials to parents in order to increase their knowledge about child development. ChCC is the most important child development public program currently operating in Chile. Due to its 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 appropriate for cognitive stimulation, as well as musical material to increase their vocabulary. In the fourth counterfactual, I analyze the effects of spending the same amount of resources as in counterfactual 1 -i.e. $$23,056 CLP a month per family- for families in the lowest income distribution, but doing so as 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 16. Initially the gaps in skills between rich and poor children are estimated at approximately of 60% of a standard deviation. We see that in-kind transfer is the most effective policy, decreasing the gap by 8%. Cash transfers and childcare subsidies decrease 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, however, increases their bagaining power so that 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 32. Additionally, women have stronger preferences for children. However, the two effects combined -the increase in their bargaining power and having stronger preferences for children- are not strong enough 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 are decomposed in Tables 36-39. Both cash transfers and childcare subsidies have an effect on employment levels. Cash transfer decreases both female and male labor force participation by less than one 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

[17] Out of the total government expenditures, 2.3% go to the preschool system compared to the average of other OECD countries, which is 1.1% (G. o. Chile, 2013).

[18] Chile Grows with You, in Spanish

in the labor market more for mothers than for fathers. Regarding monetary investments in children, cash transfers and childcare subsidies do not significantly affect this variable. Childcare subsidies increase it for two reasons. First parents spend less resources on preschool fees. 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 decreasing gaps in skills between rich and poor children.

The fact that cash transfers are not very effective at closing the gap in skills between rich and poor children is consistent with the results from 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) evaluate a cash transfer program in Ecuador using a strategy of random assignment to 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 a 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, and 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 for the aforementioned reasons, in addition to the fact that the cash transfer program included educational activities for parents that might modify their behavior. In summary, cash transfers by themselves seem to have modest effects on children's skills.

With regard to implementation of the policies, I find that childcare subsidies are cheaper than the other policies. Providing free childcare service to families is cheaper than implementing the increase in monetary or in-kind transfers to families. The information about the cost of each policy is explicitly described in Table 40. Although it is cheaper to provide childcare subsidies, at the same time, I assume that there are no general equilibrium effects as a result of the increase in demand for child care, which might generate an increase in price. Moreover, I am implicitly assuming that the available infrastructure is enough to absorb the increment in the demand. However, when we set the amount devoted to each program to be the same as the cost of providing free childcare services, the ranking in the performance of each policy is preserved. The effects of performing the same counterfactuals with the same amount of expenditure for each policy are reported in Figure 17.

7.3 Child Investments and Bargaining Power

As shown in the preliminary evidence, women spend more time with their children even when controlling for labor supply. 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 transfers should be given to women if the objective is to invest more in children. Nonetheless, this evidence is explained by several other factors.

First of all, mothers' time seems to be more productive than fathers' time, as shown by the estimation results of the model. Additionally, mothers have stronger preferences for children and the utility penalty of time investments is lower for mothers than for fathers. However, in addition to these facts, the relative empowerment of each member distorts time decisions, which explains part of the differences in time investments. Given that both parents are making investments in a public good (skills of their child) and that effort is costly and privately exerted, the fact that women spend more time with children is also a consequence of their relative disempowerment in the household rather than simply a result of different preferences.[19]

The allocation of time investments is a result of maximizing the household's welfare, which includes the skills of children, taking into account the utility penalty of time investments. The time cost of each member is not equally weighted, 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 difference 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 the child 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, whitout modifying the total amount of effort exerted by both parents. The problem is formally defined as:

$$\max_{e^f, e^m} s_2(e^f, e^m, .) \text{ subject to } e^f + e^m = e^{f,*} + e^{m,*} \tag{57}$$

where $e^{j,*}$ is the optimal solution to the maximization of the household welfare problem described in Equation 7. Define the solution to the problem in 57 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 in the production of skills should not exceed that found in the household's problem defined in 1-19. Formally:

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

[19] 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.

where the cost of effort is given by $c^j(e^j) = \alpha^j_{4,2} e^j(1+h^j)$. I call the solution to 58 $\left(e^{f,c_2}, e^{m,c_2}\right)$. In both cases, for $l = 1, 2$, we do find that:

$$\frac{\left(\frac{e^{f,c_l}}{e^{m,c_l}}\right)}{\left(\frac{e^{f,*}}{e^{m,*}}\right)} \propto \left[\frac{(1-\mu)}{\mu}\right]^{\phi/(1-\phi)} \tag{59}$$

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. If 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. I find that this mechanism explains 15% of the differences in time investments between mothers and fathers.

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, the cost of which is privately exerted, shifts into 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 the extent to which the differences observed in time spent with children are due to productivity, preferences or empowerment differences.

8 Conclusions

The way in which skills are shaped during the first years of life has significant consequences for adult life outcomes. This fact has motivated a large amount of research aimed at understanding the skill formation process in children. Some of the key facts that we have learned from the literature about the skill formation process in children are:

1. **Malleability decreases with age**. As children age, it is harder to modify, or improve, children's cognitive and non-cognitive skills.

2. **Inequalities in skills emerge very early in life**. In developing and developed countries, disparities in the process of skill formation are evident as early as when children are three years old. Children who come from poor families score systematically worse than their richer counterparts in tests and parental assessments measuring cognitive and non-cognitive skills.

3. **Parenting and general family environment largely determine the skill formation process in chil-**

dren. Early stimulation in children, coming directly from parents, has been shown to be one of the most relevant inputs in the skill formation process. Such stimulation can come in the form of time investments in children or by improving the environment of the children by improving their housing situation, the quality of the food being provided and the availability of items that promote skills, such as toys, puzzles, books and music.

4. **Parental investments in children can be complements or substitutes of public policy programs**. Given that inequalities in skills emerge very early in life, there have been multiple attempts from central governments to improve the conditions in which children live. Programs such as cash transfers, preschool subsidies and in-kind transfers have been developed with the goal of improving the quality of the environment in which children develop. However, such programs might have consequences for the way parents invest in their children, in ways that can be beneficial or detrimental for them. As an example, cash transfers might discourage female labor force participation without further increasing the amount of investments made in children, as there is no guarantee that such money will be used to improve skills in children.

Developing programs to improve the skill formation process for children in disadvantaged households should be a priority for central governments in developing and developed economies. This is one of the most efficient ways to reduce crime, improve educational outcomes and increase productivity (Cunha et al., 2010). However, when developing such programs, we need to understand what is the most efficient way to do so and how such programs affect parental investments in their children. This is the first article in the literature that empirically evaluates the effect of cash transfers, childcare subsidies and in-kind transfers on the acquisition of skills for children from disadvantaged backgrounds.

To have an accurate assessment of how such policies affect skills in children, I develop a model of household behavior and child outcomes. One of the main features of cash transfers is that they are targeted to women exclusively, with the argument that cash in the hands of women translate into better child outcomes than cash in the hands of men. To incorporate this feature, I allow parents to have different preferences about skills for children. I also allow cash transfers to have an effect on the bargaining process in the household. Additionally, I take into account that parents can invest in their children either by improving the quality of their environment via monetary investments, or by spending time with them performing activities such as reading, counting, going to cultural activities, among others.

The dataset used for this article was collected exclusively with the goal of getting a better understanding about the skill formation process in children. Thanks to that, I am able to incorporate several features of the skill formation process in children that have been ignored previously in the literature, such as parental skills, information about multiple dimensions of skills in children, quality and quantity of time and monetary investments by parents in their children, and preschool attendance, among others. This is the first paper in the literature that estimates a skill production technology via a dynamic-latent-factor structure a-là Cunha et al. (2010), nested within a model of household behavior. This allows me to obtain non-parametric identification of the skill production function. By endogenizing the investment decisions of parents, I am able to perform counterfactual policy analysis, taking into account that parents' investments in their children are distorted by government interventions.

This article proposes a new framework to estimate models of household behavior with unobserved and continuous state variables. By implementing particle filtering techniques from Machine Learning and Financial Econometrics, I demonstrate an efficient algorithm to circumvent the high-dimensionality problem. Additionally, I introduce a new estimation strategy for collective models of household behavior. Rather than using the consumption of semi-private goods within the household, I use questionnaires about female empowerment and gender roles as noisy measures of bargaining power for adult members in the household.

The results of this paper show that cash transfers have a very limited effect on reducing the gaps in skills between rich and poor children. Moreover, giving the transfers to fathers or mothers does not seem to make a significant difference. Consistent with most of the literature, I find that cash transfers have a very limited effect on female labor force participation. Childcare services have a positive but modest effect on skill promotion in children, as well as on female labor force participation. The main result suggests that the most effective way to close the gaps in skills between rich and poor children is by giving in-kind transfers. These are transfers that are given to households through a basket of goods that can be used to increase skills in their children, such as books, toys, puzzles and music. Whereas doubling the amount of monetary transfers to poor households reduces the gap in skills between children from the lowest quintile of the income distribution and their richer counterparts by about 2%, spending the same amount of resources on in-kind transfers decreases the gap by about 8%. These results are important for the design of policies to promote skills in children. Cash transfers and childcare subsidies have received significant attention in both the literature and the design of government policies. Programs that directly affect the physical environment in which children live have been less studied but seem to be more promising when it comes to increasing skills in young children.

9 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: Summary statistics

Variable	Mean	(Std. Dev.)	Min.	Max.	N
Mother's age	30.87	(7.16)	14	56	15754
Father's age	35.11	(7.76)	17	84	10564
Mother's years of schooling	11.49	(2.89)	0	21	15699
Father's years of schooling	11.41	(3.06)	0	21	10418
Mother's hours of work (week)	18.53	(21.45)	0	112	15743
Father's hours of work (week)	43.93	(15.59)	0	120	10530
Mother's weekly wage (1,000 CLP)	83.89	(92.17)	1.16	1744.19	7382
Mother's weekly wage (USD)	167.78	(184.33)	2.33	3488.37	7382
Father's weekly wage (1,000 CLP)	104.22	(144.38)	2.91	5755.81	9813
Father's weekly wage (USD)	208.44	(288.76)	5.81	11511.63	9813
Household's total Income (Weekly-CLP)	102.86	(121.75)	0	1867.44	15754
Household's total Income (Weekly (USD))	205.71	(243.49)	0	3734.88	15754
Age of child (months)	49.94	(18.04)	7	83	14183

All summary statistics are reported for the survey used in 2012.

Table 4: 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 5: 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 6: 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 7: 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 8: 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 9: 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 10: 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 11: 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 12: 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 13: Father's opinion on gender roles

Item	Number	Per cent
Women should only spend time taking care of chidlren	3,925	34.34
Women should take care of children and work if there is remaining time	6,930	60.62
Women should work full time	525	4.59
Men take care better of children than women	51	0.45
Total	11,431	100.00

Table 14: Summary statistics-Measures of bargaining power

Variable	**Mean**	**(Std. Dev.)**
A woman in charge of chores should not work	2.59	(1.03)
Both parents should contribute equally to household income	1.85	(0.95)
It is better if the man goes to work and the woman stays at home	2.57	(1.06)
Men should be more involved in household chores	1.84	(0.99)
If husband earned enough there is no reason for woman to work	2.55	(1.6)
It is better if woman has children after having a succesful carreer	2.45	(1.25)
It is very important for a woman to have a job	1.94	(1.06)
Having a job is the best way for a woman to achieve independence	1.86	(0.98)
Father's time is as important as mother's time for children	1.56	(0.87)
It is better to have a bad marriage than being single	3.57	(1.4)
N	15754	

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 15: Summary statistics-Variables determining Pareto weight

Variable	**Mean**	**(Std. Dev.)**	**N**
Father's non-labor income share	0.27	(0.34)	4470
Age difference (Father-Mother)	3.01	(5.18)	4470
Difference in grades attained (Father-Mother)	-0.21	(2.82)	4470
Sex ratio in region (Women/Men)	1.01	(0.06)	4470
Unemployment ratio in region (Men/Women)	0.67	(0.11)	4470
Wage ratio in region (Men/Women)	1.41	(0.07)	4470
Distance to women protection center (km)	19.15	(31.79)	4465

The ratio of wages offered is not reported in these table as is the results of the parameters estimated in the model. The share of father's non-labor income, as well as the age difference and the differences in grades attained are all obtained from the ECLS dataset. The sex ratio in the city is computed using information from the CENSUS dataset. The last CENSUS available for Chile is from 2002. I use information about female-male ratio based on the population projections from the National Institute of Statistics fro Chile. The unemployment and wage information is obtained from the CASEN household survey of 2011.

Table 16: Time investments and labor supply (2010)

VARIABLES	(1) Mother's effort (2010)	(2) Father's effort (2010)
Mother: hours worked weekly	-0.00***	0.00***
	(0.00)	(0.00)
Father: hours worked weekly	0.00***	-0.00***
	(0.00)	(0.00)
Total household income	0.00	0.00***
	(0.00)	(0.00)
Age of child (months)	0.01***	0.00*
	(0.00)	(0.00)
BFI-Extraversion	0.05***	0.07***
	(0.02)	(0.02)
BFI-Kindness	0.05**	0.04*
	(0.02)	(0.02)
BFI-Responsibility	0.06***	0.05**
	(0.02)	(0.02)
BFI-Neuroticism	-0.05***	-0.02
	(0.01)	(0.02)
BFI-Openness	0.15***	0.02
	(0.02)	(0.02)
Wais-digits	0.01	0.01*
	(0.01)	(0.01)
Wais-Vocabulary	-0.00	-0.00
	(0.00)	(0.00)
Number of siblings	-0.07***	-0.06***
	(0.01)	(0.01)
Observations	7,058	7,058
Adjusted R-squared	0.07	0.04

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Additional controls include age of child, race, age of both parents and test scores of primary caregiver.

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, together with the big five personality test scores and the Wais cognitive assessments are all standardized to have mean zero and one standard deviation. In the regression the measure of effort is in hundreds.

Table 17: Time investments and labor supply (2012)

VARIABLES	(1) Mother's effort (2012)	(2) Father's effort (2012)
Mother: hours worked weekly	-0.01***	0.00***
	(0.00)	(0.00)
Father: hours worked weekly	0.00	-0.01***
	(0.00)	(0.00)
Total household income	0.00	0.00
	(0.00)	(0.00)
Age of child (months)	0.01***	0.00***
	(0.00)	(0.00)
BFI-Extraversion	0.01	0.05*
	(0.03)	(0.03)
BFI-Kindness	0.06	-0.00
	(0.04)	(0.03)
BFI-Responsibility	0.11**	0.11***
	(0.04)	(0.03)
BFI-Neuroticism	-0.05	-0.04
	(0.03)	(0.03)
BFI-Openness	0.19***	0.05*
	(0.04)	(0.03)
Wais-digits	-0.02	-0.00
	(0.01)	(0.01)
Wais-Vocabulary	0.01***	0.01***
	(0.00)	(0.00)
Number of siblings	-0.09***	-0.06***
	(0.02)	(0.02)
Observations	8,020	7,956
Adjusted R-squared	0.04	0.03

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Additional controls include age of child, race, age of both parents and test scores of primary caregiver.

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, together with the big five personality test scores and the Wais cognitive assessments are all standardized to have mean zero and one standard deviation. In the regression the measure of effort is in hundreds.

Table 18: Regressions of effort in differences

VARIABLES	(1) ΔEffort father	(2) ΔEffort mother
ΔHours worked mother	0.03***	-0.02***
	(0.01)	(0.01)
ΔHours worked father	-0.03***	0.01**
	(0.01)	(0.01)
ΔEffort mother	0.37***	
	(0.01)	
ΔEffort father		0.36***
		(0.01)
Observations	4,531	4,531
R-squared	0.14	0.15

*** p<0.01, ** p<0.05, * p<0.1.
Standard error in parentheses.

$\Delta X = X_{2012} - X_{2010}$. The measure of effort is the same used as in Table 17 but in differences. The same controls as in Table 17 are used.

Table 19: Child outcomes in 2012 and share of income earned by women

VARIABLES	(1) Motor skills 2 (B3)	(2) Cognitive test (B5)	(3) Batelle Total	(4) Vocabulary test	(5) TADI Socioemotional	(6) TADI-motor	(7) TADI-cognitive
Mother's income share	0.09*	0.09*	0.10**	0.12**	0.10**	0.12**	0.15***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Total household income	0.00	0.00**	0.00**	0.00***	0.00***	0.00	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Mother's years of schooling	0.01**	0.02***	0.03***	0.03***	0.03***	0.02***	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Father's years of schooling	0.02***	0.01**	0.02***	0.03***	0.01**	0.01	0.02***
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)
Number of siblings	0.02	-0.00	-0.03*	-0.07***	-0.05***	-0.02	-0.07***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Age of child (months)	0.00***	0.00***	0.01***	0.01***	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
BFI-Extraversion	0.06***	0.04**	0.04***	0.03*	0.04**	0.01	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
BFI-Kindness	-0.00	0.09***	0.02	0.01	0.03	0.03	-0.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
BFI-Responsibility	0.10***	0.08***	0.07***	0.04*	0.06**	0.03	0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
BFI-Neuroticism	-0.02	-0.03*	-0.01	0.00	0.02	0.01	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
BFI-Openness	0.07***	0.03	0.03	-0.03	-0.02	-0.01	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Wais-digits	0.01	0.01	0.02***	0.01**	0.02***	0.02***	0.02***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Wais-Vocabulary	0.00	0.00***	0.00***	0.01***	0.00***	0.00	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	6,823	6,823	6,822	6,915	6,870	6,849	6,860
Adjusted R-squared	0.03	0.05	0.08	0.10	0.06	0.02	0.10

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 20: 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	0.00***	0.00	-0.00*	0.00	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Mother's years of schooling	0.01***	0.01**	-0.01	0.01*	-0.03***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)
Father's years of schooling	0.01***	0.01**	-0.00	-0.00	-0.02***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
Number of siblings	0.00	0.04**	0.01	0.00	0.08***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
People in household	-0.01**	0.01	0.01	0.02*	0.13***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Woman administers+	0.03**	0.09***	-0.04*	0.08***	-0.00
	(0.01)	(0.02)	(0.02)	(0.03)	(0.02)
Gender roles -Woman++	-0.01	-0.03**	0.02	-0.02	0.02*
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Gender roles - Man++	-0.01	-0.05*	-0.04	-0.02	0.06**
	(0.01)	(0.03)	(0.03)	(0.03)	(0.02)
Observations	6,344	8,245	8,242	8,241	8,246
Adjusted R-squared	0.04	0.03	0.02	0.01	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 11. + 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 21: 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 22: 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

All summary statistics are reported for the survey used in 2012.

Table 23: Age distribution (2012)

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

Table 24: 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 25: 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 26: 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 27: 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 28: 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 29: 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 30: Estimates: Distribution of latent factors

Parameter	Estimate	Standard Error
σ^m_{ef}	2.5133	0.0039
σ^f_{ef}	3.3754	0.0025
σ_{inv}	2.1896	0.0144

Table 31: 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 32: 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 33: Model Fit - I

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

Table 34: Model Fit - II

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

Table 35: Model Fit - III

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

Table 36: 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 37: 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 38: 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

Table 39: 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

Table 40: Cost of policy interventions

Counterfactual	Expenditure per capita (USD)
Transfers to Mother	449.59
Transfers to Father	449.59
Childcare Subsidy*	221.64
In-kind transfers	449.59

Figure 1: Information on Preschool Providers

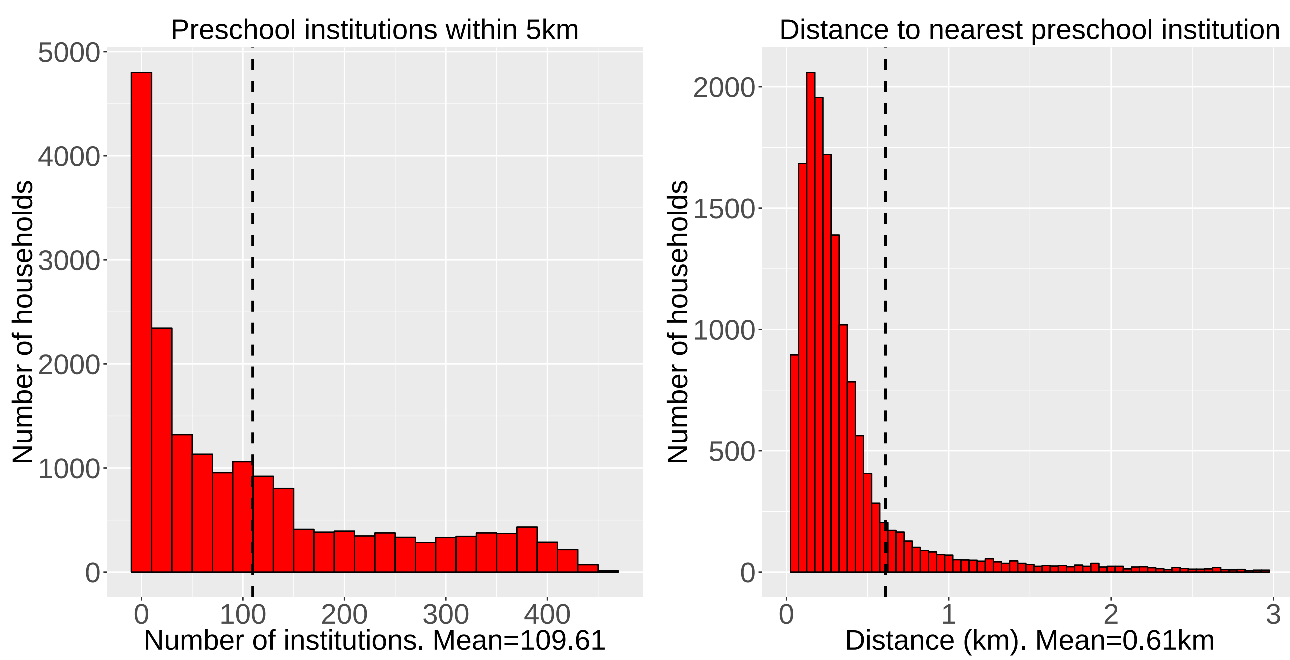
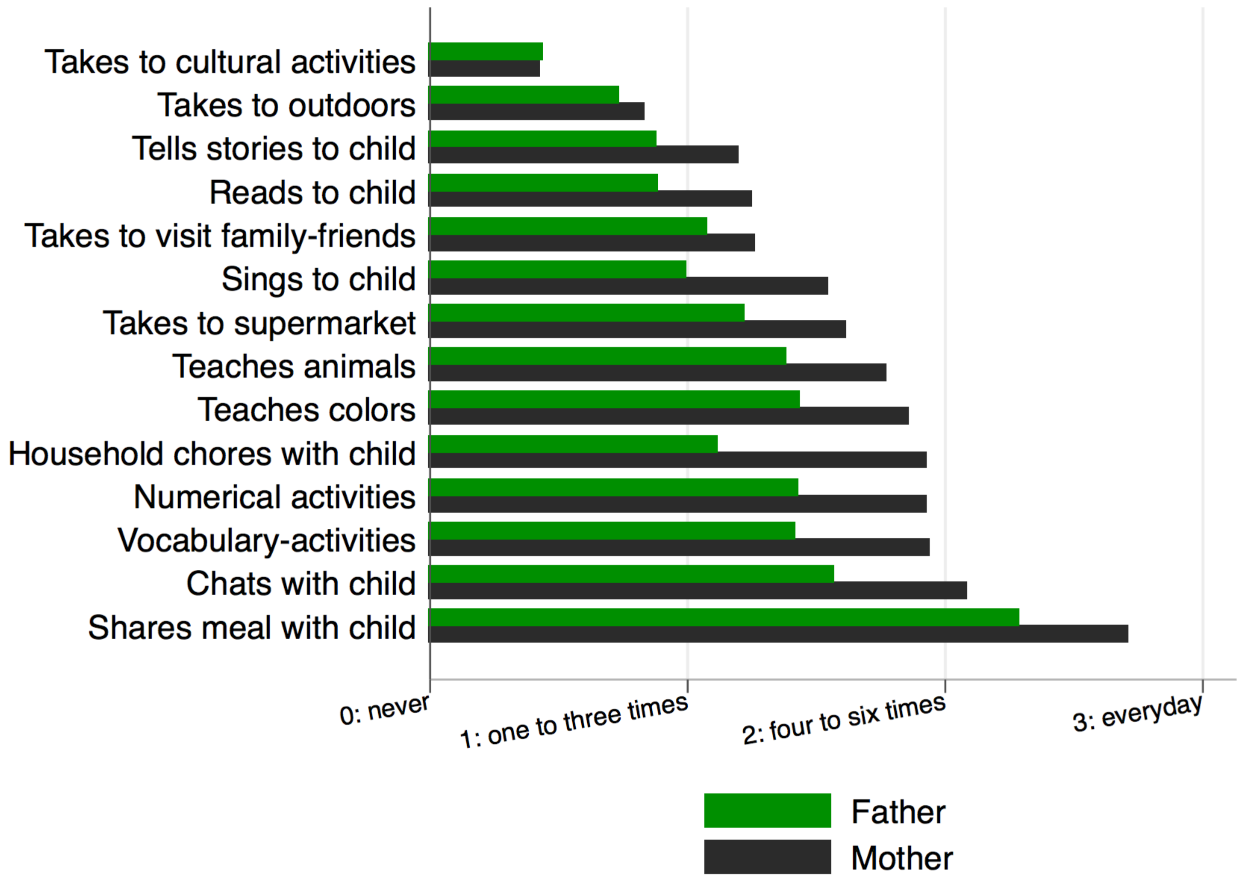


Figure 2: Example of distribution of childcare providers. City of “La Serena”, Chile

Figure 3: 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 4: Female Labor Force Participation (%)

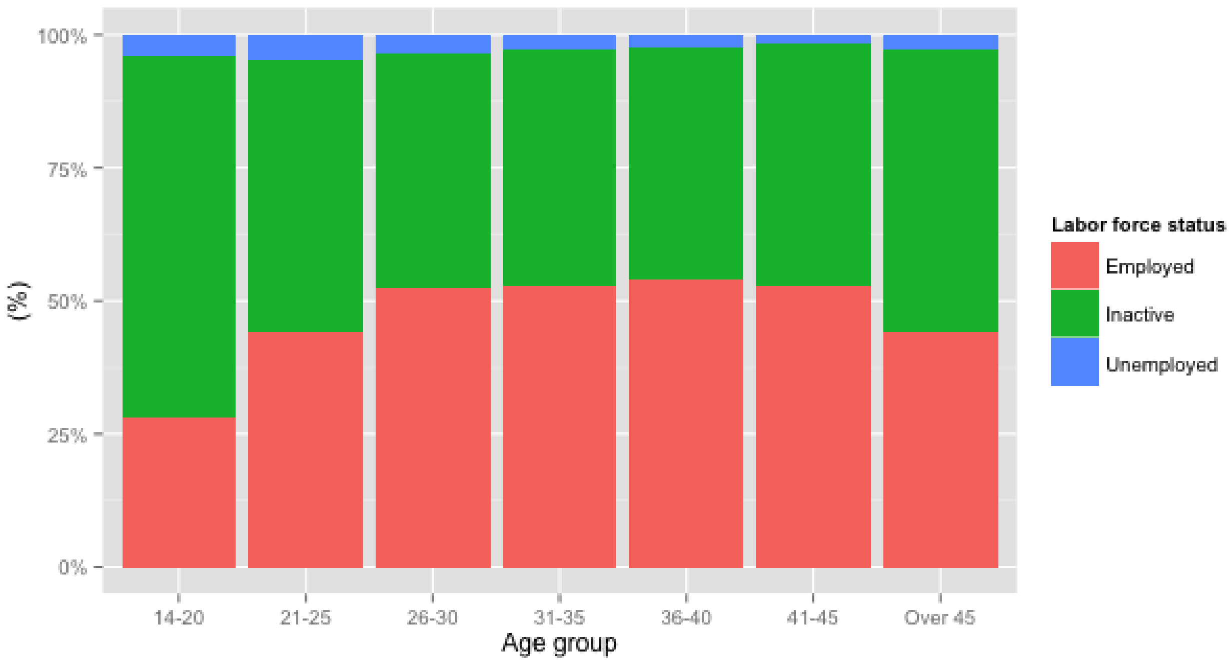


Figure 5: Gaps in health at birth (%)

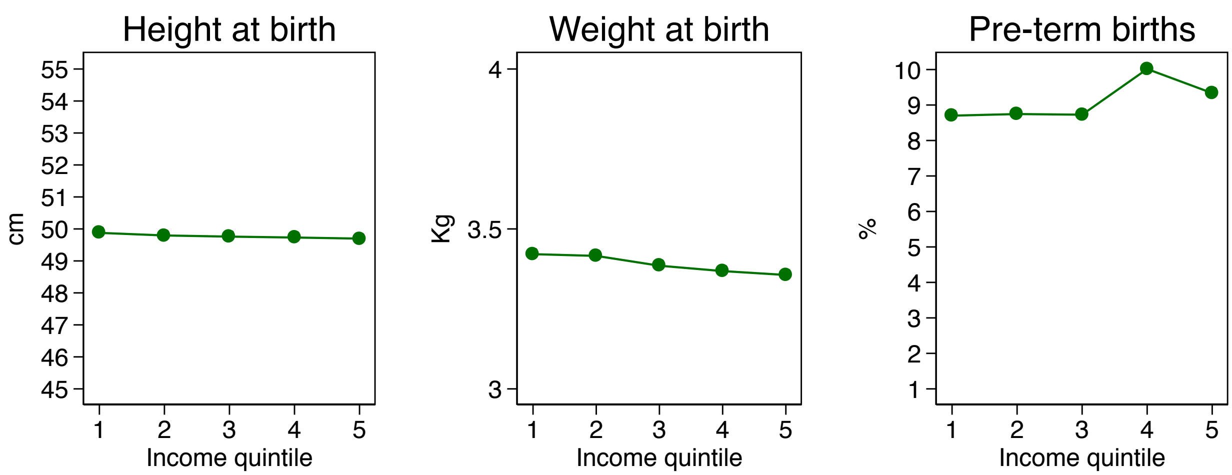
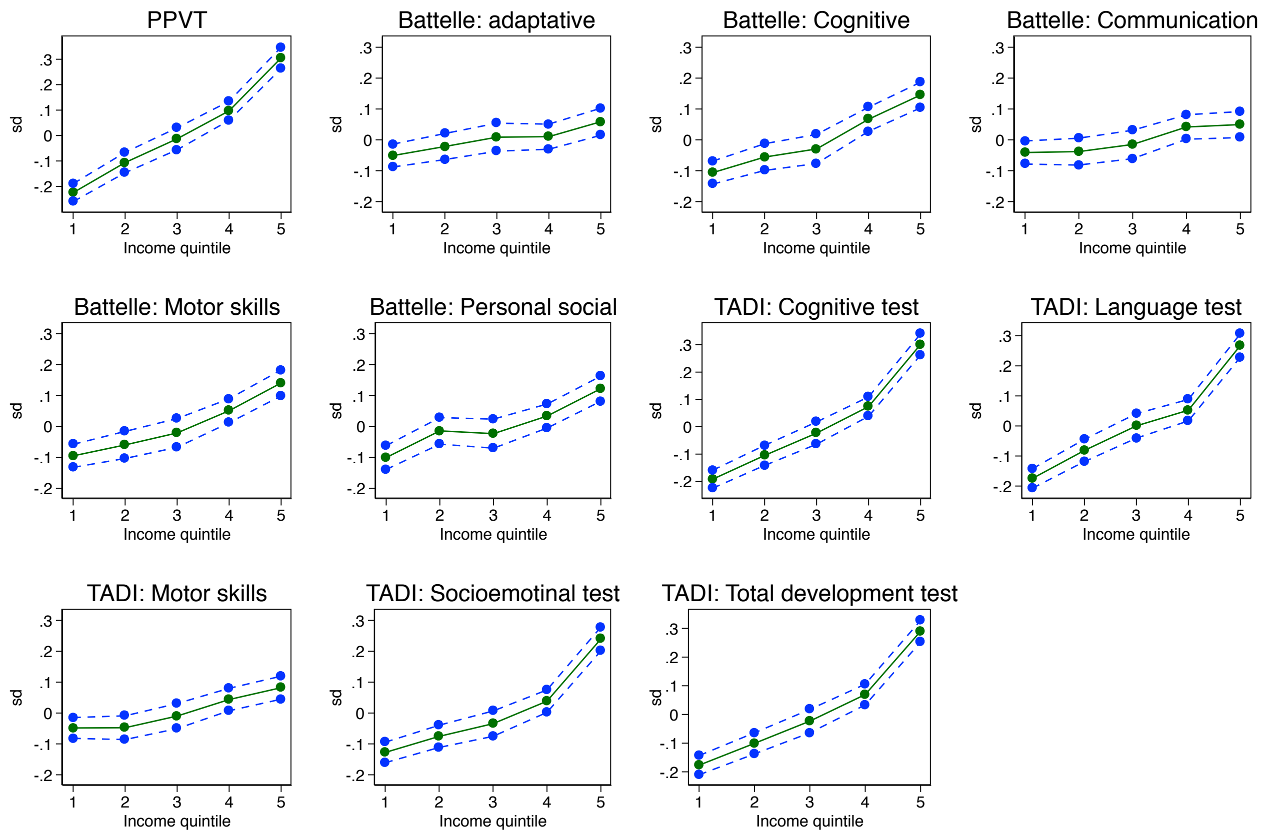


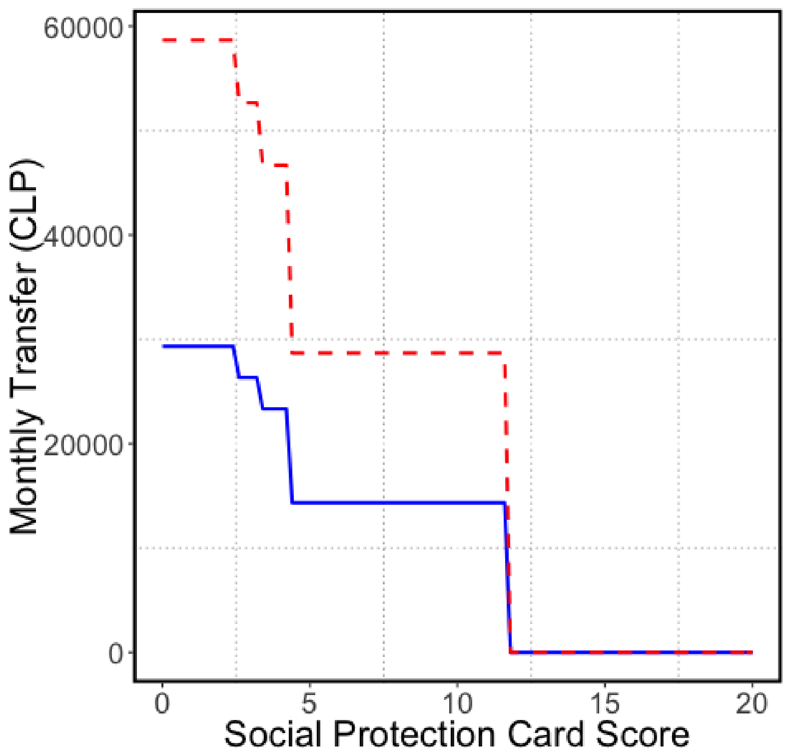
Figure 6: Gaps in skills at age 5



The green (solid) line is the mean score, the blue (dashed) line is the 95% confidence interval. 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.

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

Figure 7: Monetary Transfers to Families in Chile



The graph reports the relationship between monetary transfers that families receive from the central government, on a monthly basis, from three main programs: "Unique Family Subsidies"[a], "Family Assignments"[b] and "Social Protection Transfer"[c] and their score in the Social Protection Card[d]. The conditions to be eligible for these programs are to have a score in the Social Protection Card below 11.734 and for those who work, having a monthly income of less than $187,515 CLP. The final amount being transferred to the household also depends on the size of the household and the time they have been beneficiaries of such programs. The solid line represents the schedule for a family composed of two adults and one child who has been in the program for 50 months. The dashed line corresponds to a bi-parental household with three children under 18 who have been in the program for less than six months.

[a]"Asignación Única Familia" in Spanish.
[b]'Asignación Familiar" in Spanish
[c]"Bono de protección social"
[d]"Ficha de Protección Social"

Figure 8: Model fit: Female labor force participation according to education

Figure 9: Model fit: Male labor force participation according to education

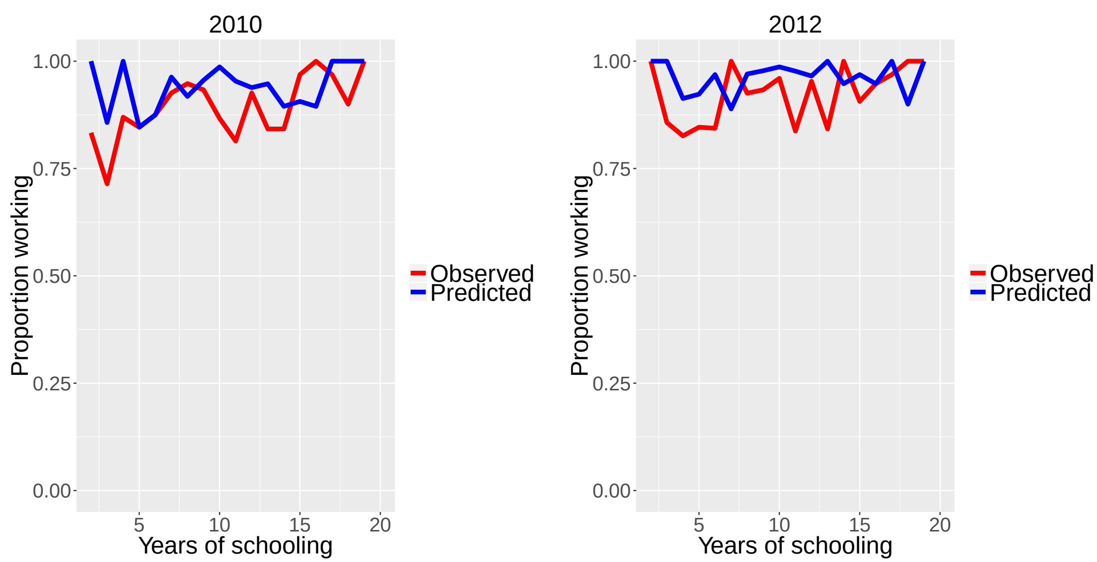
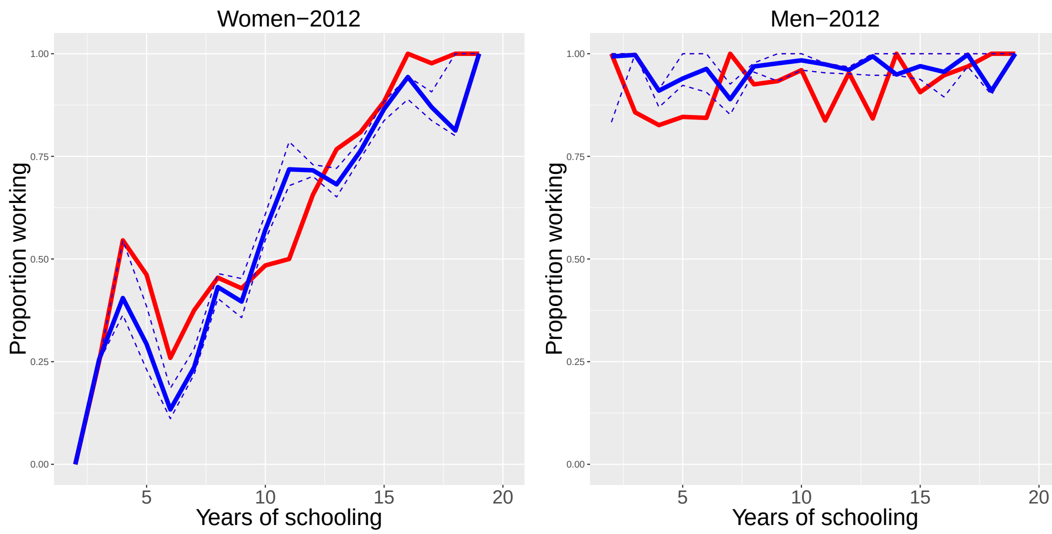
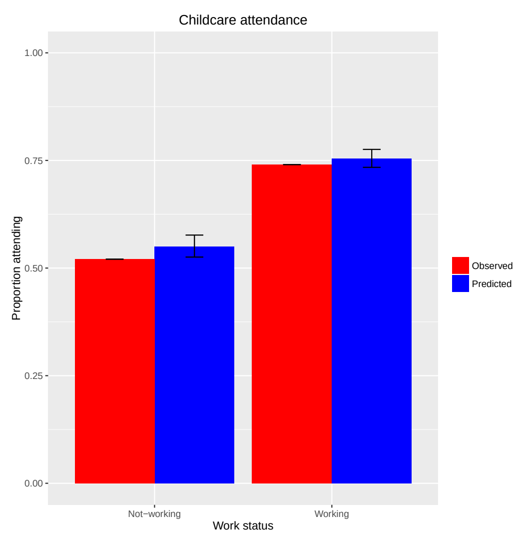


Figure 10: Bootstrap fit: Parents' Labor Force Participation in 2012



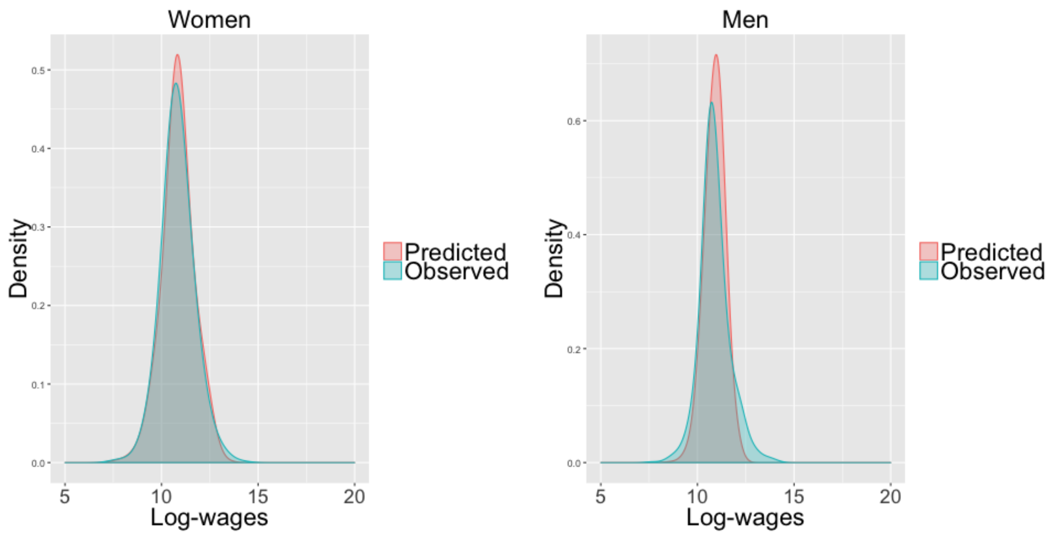
Dashed lines represent the 95% confidence interval

Figure 11: Bootstrap fit: Childcare decisions (%)



Brackets include the 95% confidence interval

Figure 12: Model fit: distribution of wages



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

Figure 13: Distribution of skills. Smoothing distribution

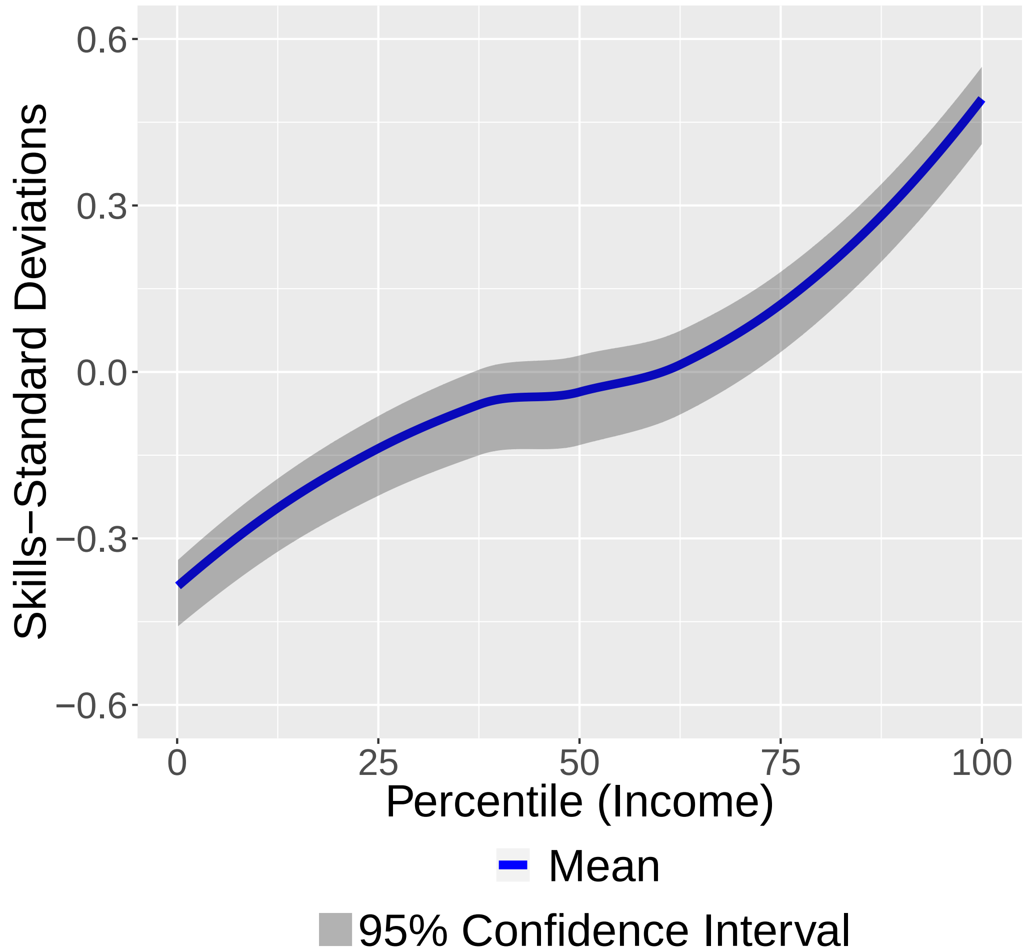


Figure 14: Signal to noise ratio. Mother's effort (2012)

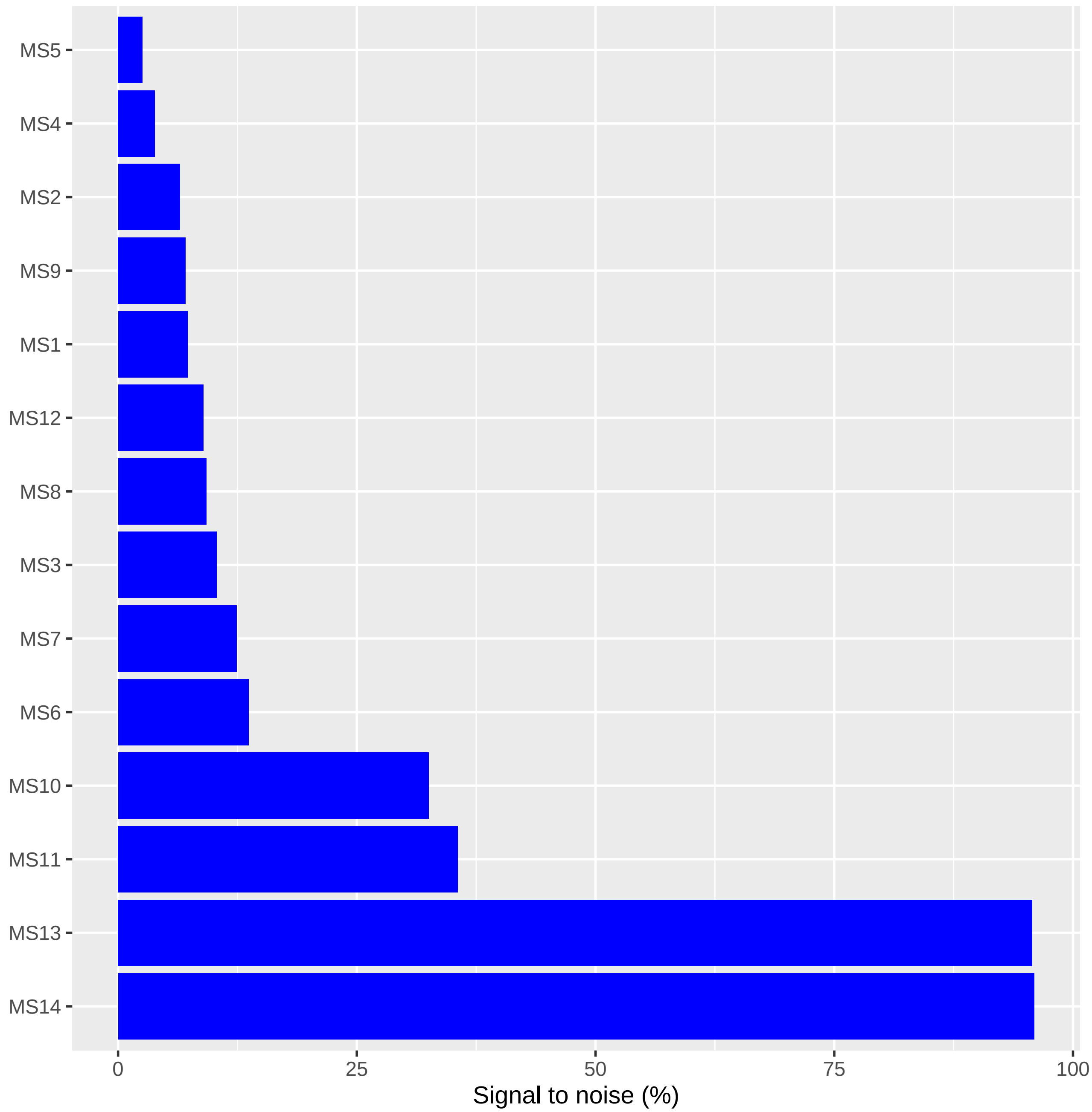


Figure 15: Signal to noise ratio. Monetary Investment (2012)

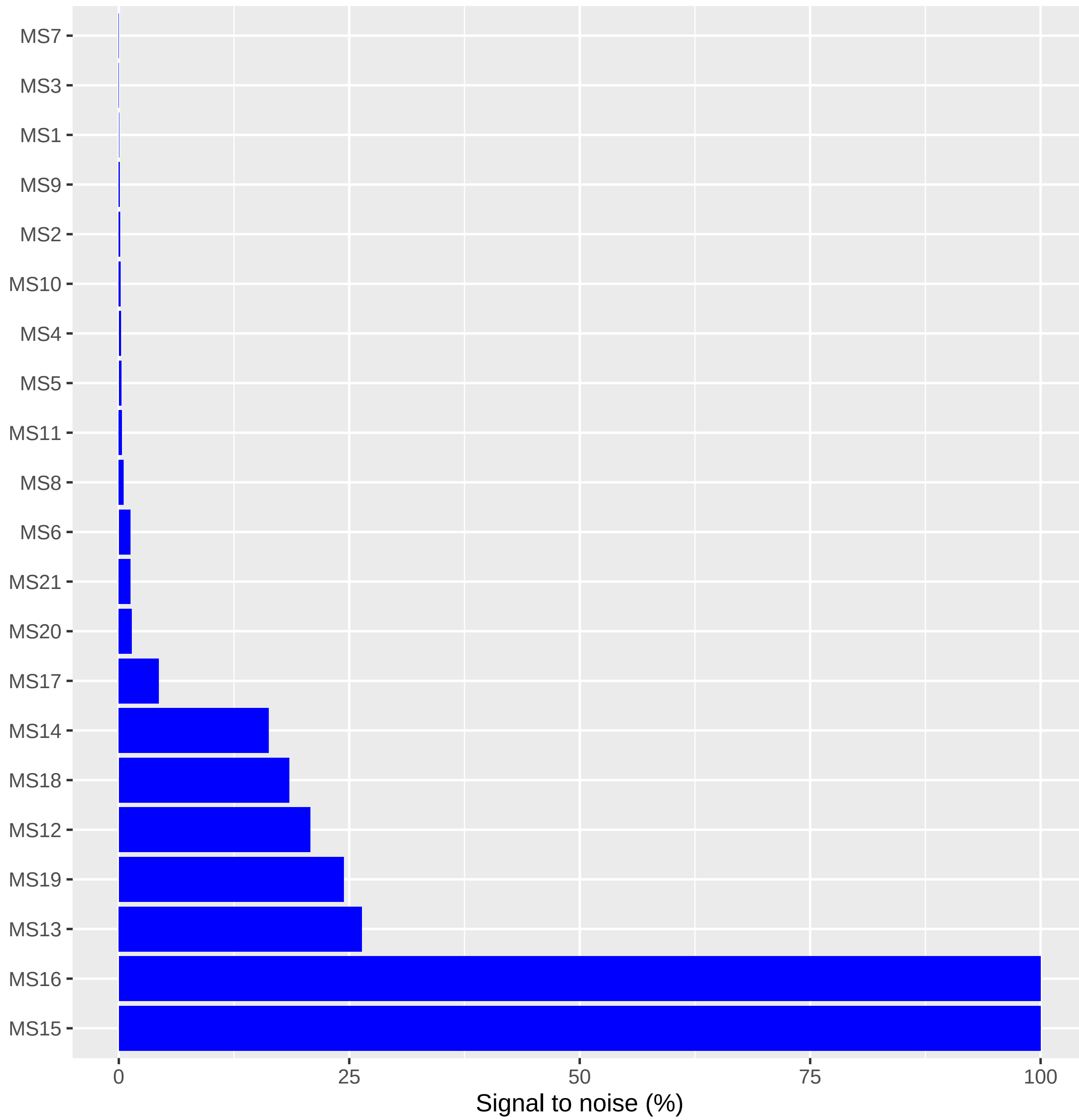


Figure 16: Effects of Policy Interventions

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

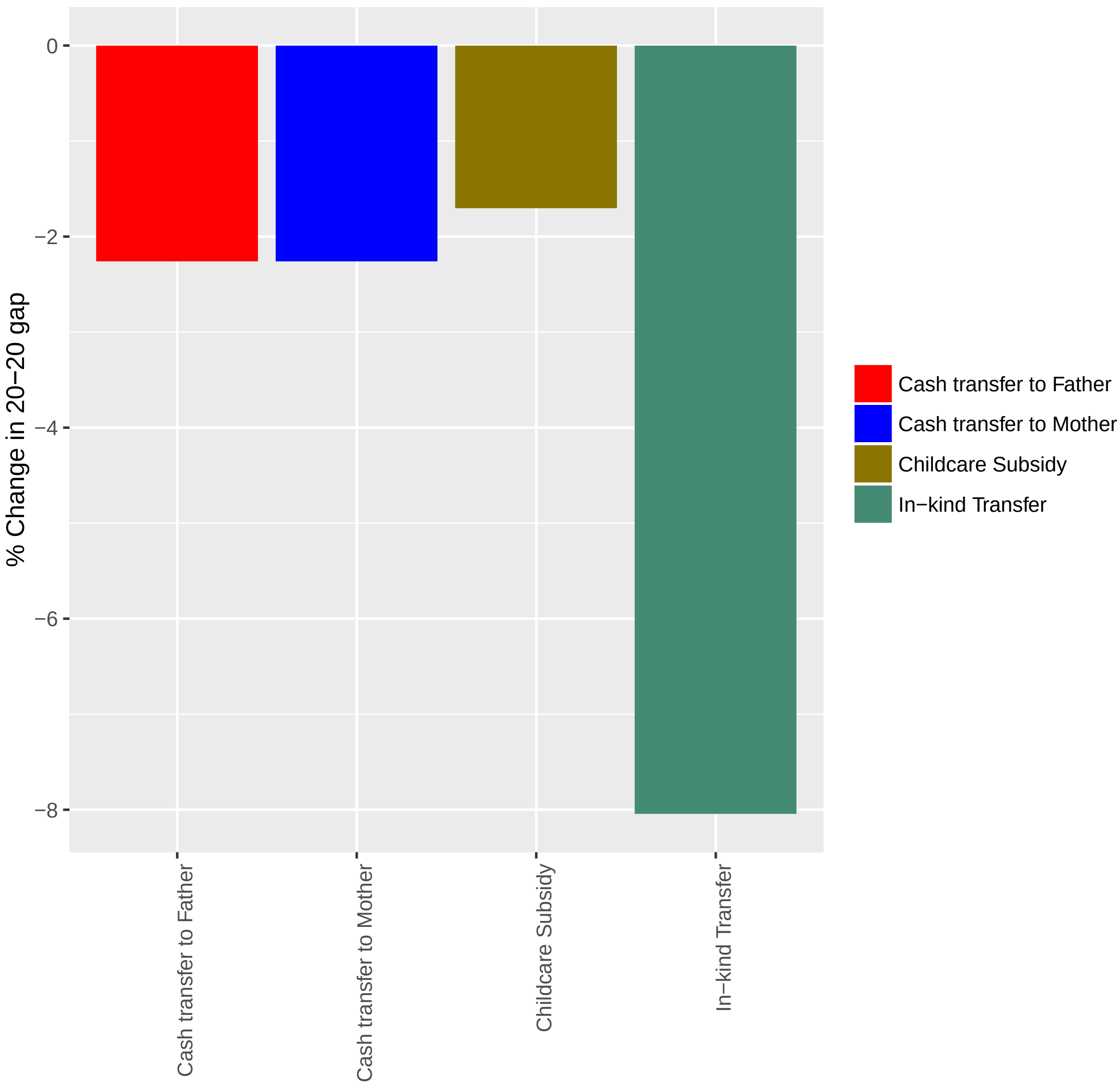
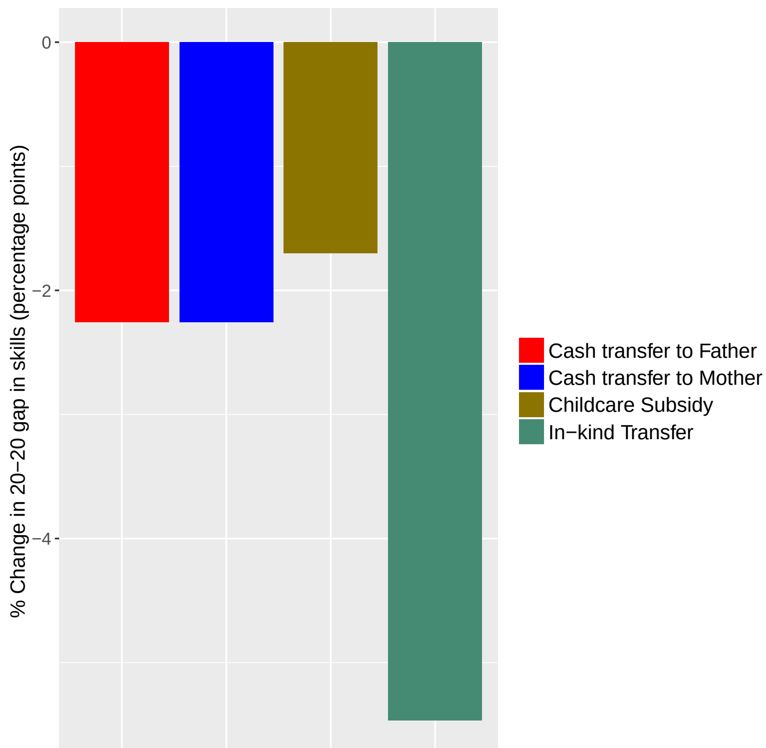


Figure 17: Effects of Policy Interventions

Effects on the gap in skills between the top 20% richest households and the poorest 20% of the households when money spent in each policy is the same.



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10 Appendix

10.1 Identification of Measurement System

The measurement system is described by:

$$Z = \iota_0 + \iota_1 K + \boldsymbol{\varepsilon} \tag{60}$$

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

$$\Sigma_Z = \iota_1 \Sigma_K \iota_1' + \Sigma_\varepsilon \tag{61}$$

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:

$$M = \sum_{k \in K} N_k = 151 \tag{62}$$

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.

10.2 Estimation

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

10.2.1 Likelihood function

The likelihood of the model is:

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

$$p_0(O_0|\Theta, X)p_1(O_1|O_0, \Theta, X)p_2(O_2|O_1, \Theta, X) \tag{63}$$

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.

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

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

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

$$\sum_{rr=1}^{RR} P_0(O_0|K_0^{\{rr\}}, \Theta, X) \tag{64}$$

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

$$K_0 = \{\ln(s_0), \ln(PG)\} \tag{65}$$

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 $\sigma^2_{s_0}$ and σ^2_{PG} 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:

$$K_1 = \{\ln(s_1), \ln(e_1^{f,*}), \ln(\hat{e}_1^{m,*}), \ln(I_1^*), \mu_1\} \tag{66}$$

and the likelihood can be expressed as:

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

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

$$\int\int p_1(O_1|K_1,K_0,O_0,\Theta,X)p(K_1|O_0,K_0,\Theta,X)p(K_0|O_0,\Theta,X)dK_1dK_0 \quad (67)$$

Note that

$$p(K_1|O_0,K_0,\Theta,X) = p(K_1|K_0,\theta,X) \quad (68)$$

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

$$p_1(O_1|K_1,K_0,O_0,\Theta,X) = p_1(O_1|K_1,\Theta,X) \quad (69)$$

Taking into account the facts presented in Equations 68 and 69 we can express 67 as:

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

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

$$E_{p(K_0|O_0,\Theta,X)}\left[\int p(O_1|K_1,\Theta,X)p(K_1|K_0,\Theta,X)dK_1\right] = \quad (70)$$

in Equation 70 $p(O_1|K_1,\Theta,X)$ 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:

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

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

$$\times\, p(h^{f,*},h^{m,*},a|w^f,w^m,K_1,\Theta,X) \quad (71)$$

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:

$$\ln\left(w^j\right) = \beta_0^j + \beta_1^j yrschool^j + \beta_2^j Age^j + \beta_3^j (Age^j)^2 + \varepsilon_{w^j} \quad (72)$$

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:

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

$$p_{(\varepsilon_d^f, \varepsilon_d^m)}\left(W(u^f(h^{f*}, h^{m,*}, a^*), u^m(h^{f,*}, h^{m,*}, a^*)) \in \arg\max_{\{h^f, h^m, a\}} W(u^f(h^f, h^m, a), u^m(h^f, h^m, a))|K_1, \Theta, X\right) \tag{73}$$

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

$p(K_1|K_0, \Theta, X)$ 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:

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

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

$$p(\ln(s_1)| \ln(e_1^{f,*}), \ln(e_1^{m,*}), \ln(I_1^*), \mu_1, \ln(PG), \ln(s_0), \Theta, X) \tag{74}$$

$$\times\, p(\ln(e_1^{f,*})|\mu_1 \Theta, X) \tag{75}$$

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

$$\times\, p(\ln(I_1^*)|\mu_1, \Theta, X) \tag{77}$$

$$\times\, p(\mu_1|\Theta, X) \tag{78}$$

The term 74 is given by the production of skills and the remaining 75-77 are given by the distribution of heterogeneity in each factor: η_{e^f}, η_{e^m} and η_I. The term 78 is given by the distribution of heterogeneity in 14. Note that we can also use Monte-Carlo techniques to approximate the expression in 70 by:

$$\sum_{rr=1}^{RR} \hat{w}_0^{\{rr\}} \left[\int p(O_1|K_1, \Theta, X) p(K_1|K_0^{\{rr\}}, \Theta, X) dK_1\right] \tag{79}$$

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:

$$\hat{w}_0^{rr} = \frac{w_0^{rr}}{\sum_{rr=1}^{RR} w_0^{rr}} \tag{80}$$

and the individual weights are defined:

$$w_0^{rr} \propto \frac{p(K_0|O_0, \Theta, X)}{g_0(K_0|\mathcal{Z}_0, \theta_0, \Theta, X)} \tag{81}$$

Note that after some algebra, we can define:

$$\tilde{w}_1 = \frac{p(O_1|K_1, \Theta, X)p(K_1|K_0, \Theta, X)}{g_t(K_0|, O_0, O_1, \Theta, X)} \tag{82}$$

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 82 into 70 we obtain:

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

$$\sum_{rr=1}^{RR} \hat{w}_0^{\{rr\}} \left[\sum_{rr'=1}^{RR} \tilde{w}_1^{rr'}(rr) \right] \tag{83}$$

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:

$$p_1(O_1|K_1, K_0, O_0, \Theta, X) = \sum_{rr=1}^{RR} \hat{w}_0^{rr} \tilde{w}_1^{rr} \tag{84}$$

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).

10.3 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 18: Particle Filtering Algorithm

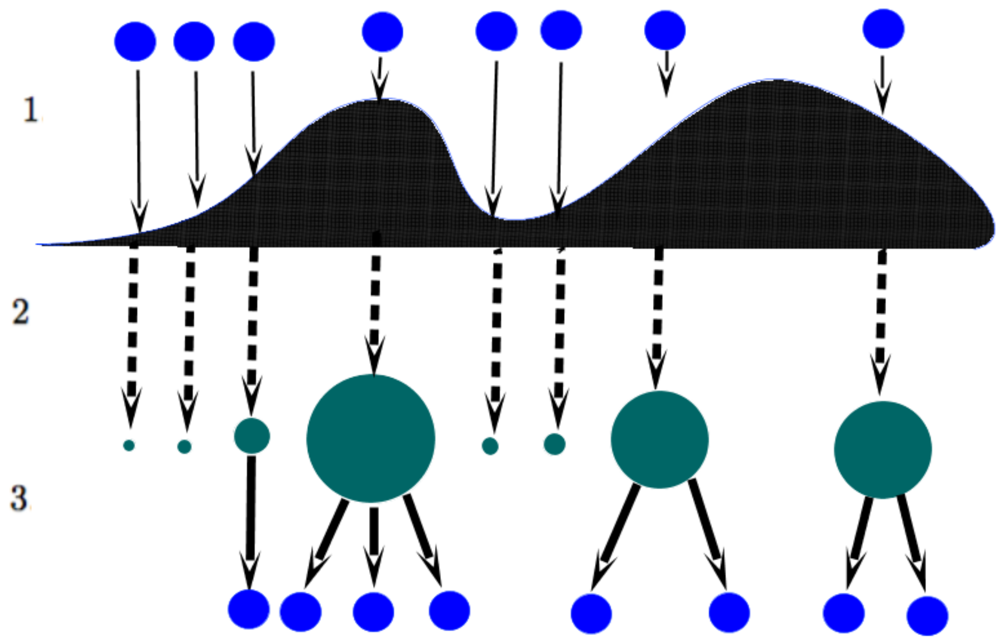


Figure 18 illustrates the particle filtering algorithm with eight particles. In the first step, particles are drawn from the proposal distribution $g(K_0|\Theta, X)$. In the second step, the likelihood of each particle is evaluated through the likelihood system $P_0\left(O_0|K_0, \Theta, X\right)$. In 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.

10.4 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 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:

$$p(K_t|O_{0:2}) \tag{85}$$

where we basically condition on all the measures we have. Note that we can write Equation 85 as:

$$p(K_t|O_{0:2}) = p(K_t|O_{0:t}) \int \left(\frac{p(K_{t+1}|O_{0:2})p(K_{t+1}|\theta_t)}{\int p(K_{t+1}|\theta_t)p(K_1|O_{0:t})dK_t} \right) dK_{t+1} \tag{86}$$

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

$$\hat{p}(K_t|O_{0:2}) = \sum_{rr=1}^{RR} w_{t|T}^{(rr)} \delta_{K_t^{(rr)}}(K_t) \tag{87}$$

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

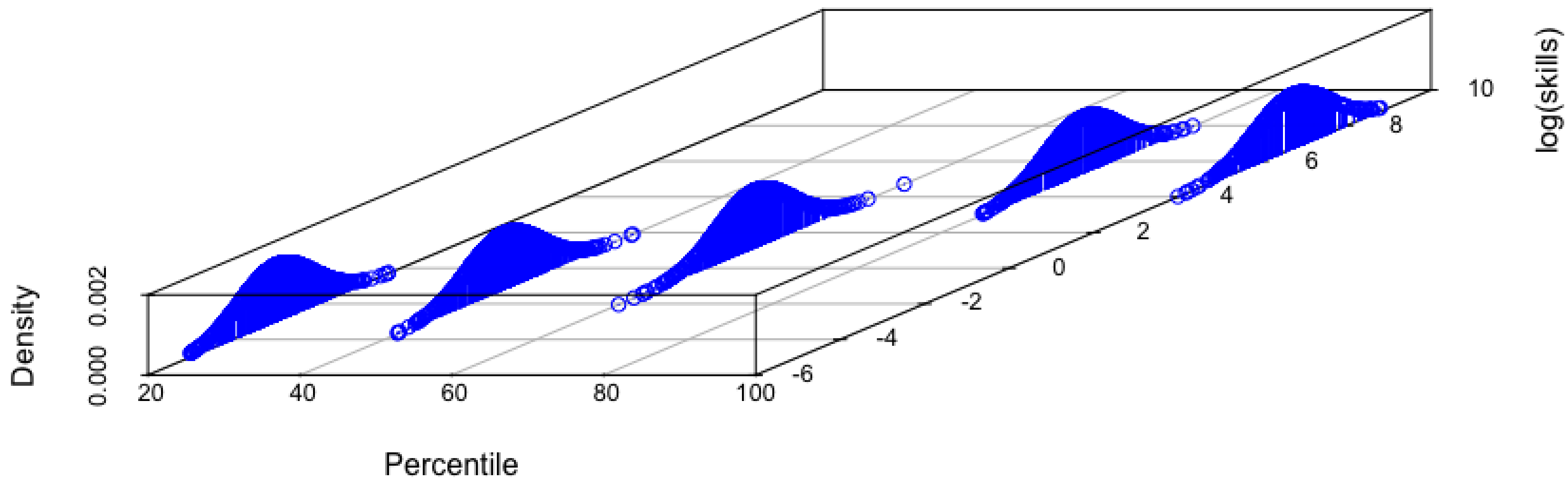
$$w_{t|T}^{(mm)} = w_t^{(mm)} \left[\sum_{rr=1}^{RR} w_{t+1|T}^{(rr)} \left(\frac{p\left(K_{t+1}^{(rr)}|K_t^{(mm)}\right)}{\sum_{kk=1}^{KK} w_t^{(kk)} p\left(K_{t+1}^{(rr)}|K_t^{(kk)}\right)} \right) \right] \tag{88}$$

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 19: 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 13

10.5 Cash Transfer Programs in Chile

The basic program through which poor families receive cash transfers from the central government is the "Unique Family Subsidy".[20] Such program established a monthly transfer of $14,340 CLP in 2012, for a family in conditions of vulnerability[21] with one child.[22] 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.[23]

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] Subsidio Unico familiar in Spanish.

[21] 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

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

[23] 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.