

# Parental Decisions and Child Outcomes

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## Abstract

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

## 1 Introduction

Research in medicine, psychology and economics, shows that the way skills are formed during the first years of life has significant consequences on adult life outcomes<sup>1</sup>. This fact has motivated a large number of studies aimed at identifying the determinants of having an adequate early childhood development. Some of the results of such studies have allowed us to get a better understanding of which are the key inputs to promote skills in young children<sup>2</sup>. For instance, we know that parenting and general family environment are amongst the most relevant inputs in the production of skills (J. Heckman & Mosso, 2014; Schoellman, 2014). However, having a good

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<sup>1</sup>For a review see [Conti and Heckman \(2012\)](#)

<sup>2</sup>See, for example, [Cunha, Heckman, and Schennach \(2010\)](#)

characterization of the production function is not enough to assess the effectiveness of policies aimed at improving skills of children. Families administer the resources and make the relevant decisions that determine the allocation of inputs for young children. For that reason, in order to fully understand the consequences of public policies on the skills of young children, we need to get a better understanding of how families decide on the allocation of resources for their children.

In this article, I use a rich dataset of early childhood development from Chile, in order to estimate a production function of skills, nested within a collective model of household behavior. I find that there are substantial disparities in skills between rich and poor children when they are five years old. The results of the estimation exercise are used to assess the effects that different policy interventions have on the skills of young infants. The policies that I simulate are unconditional cash transfers, free childcare and in-kind transfers of goods to promote child skills, such as toys, books and puzzles, to disadvantaged families. The results show that in-kind transfers are much more effective than the two other alternatives when it comes to closing the gaps in skills between rich and poor children. Cash transfer programs usually set as an explicit requirement that it should be the mother, rather than the father or other family member, the person who receives the benefit. Nonetheless, I find that it makes no much difference when the father, rather than the mother, is set as the recipient of such transfers.

Cash transfer programs have become a very popular tool in developing countries as a way to alleviate poverty (Fiszbein, Schady, & Ferreira, 2009). However, I find that cash transfers to poor households accomplish close to nothing when it comes to closing the gaps in skills between rich and poor children. Such policies usually set as an explicit condition that the mother of the child should be the recipient of the transfer, the argument being that cash in the hands of women translates into better child outcomes than cash in the hands of men (Doepke & Tertilt, 2014). Nonetheless, when I simulate the cash transfer program having the father as the recipient, the effects of such program do not change significantly.

Free childcare - preschool policies have also been very popular not only as a way to promote skills in young children but also to promote female employment. In 2013, the government of Chile established free and mandatory preschool services for children older than five years of age. In part because of that, Chile is now the country with the highest expenditure in preschool system as a share of total government expenditure, of countries in the OECD<sup>3</sup>. In this paper I simulate a free childcare system for households in the lowest income quintile. The results shows that this policy increases female labor force participation mildly, but have very limited effects on the acquisition

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<sup>3</sup>Out of the total government expenditures, 2.3% go to the preschool system as opposed to the average of other OECD countries, which is 1.1% (Chile, 2013)

of skills of young children.

Even though cash transfer programs and childcare subsidies seem to be ineffective when it comes to closing the gaps in skills between poor and rich children, I find that setting up a system of in-kind transfer where the government gives goods aimed at improving skills of children, such as puzzles, toys, or food for children, has an enormous potential. When standardizing the stock of skills for children who are five-six years old, those located in the lowest quintile of the income distribution have, on average, one standard deviation below the average of those children located in the richest income quintile. Cash transfer programs and childcare-preschool subsidies reduce this gap in approximately 5%. However, in-kind transfers diminish this gap in approximately 15%.

The article that is most related to this paper is probably [Del Boca, Flinn, and Wiswall \(2014\)](#). However, the dataset used in this article allows me to take into account some key elements in the process of child development that are ignored in the aforementioned article. First of all, there is a consensus in the literature stating that skills are multiple (emotional, physical, cognitive) and that they interact with each other in the process of skill formation. In this article, rather than using one cognitive test score as a measure of skills, I use various indicators of motor development, cognitive achievement and emotional attainment in young children. Additionally, an important element in the process of skills formation in children is their dependance on parental skills ([Francesconi & Heckman, 2016](#)). Ignoring the skills of parents in the estimation of a production of skills in young children might bias the effect that other inputs have, such as time or in-kind investments. I overcome this limitation by using assessments of cognitive achievement and personality traits of parents. Moreover, an important decisions that families need to make and that have significant consequences in the acquisition of skills in young children is when, and whether or not, children should attend childcare or preschool. I observe such decision in the dataset and am able to simulate policies that aimed at subsidizing the price of childcare or preschool services. Furthermore, I observe decisions of investments in children, different to time spent with parents, such as availability of toys, books, how adequate is the dwelling to raise a child, among others, and because of that, I am able to consider a broader spectrum of investment decisions in children.

In the preceding paragraph I mentioned some elements in which the analysis of this paper and [Del Boca et al. \(2014\)](#) differ. Nonetheless, I consider that the main points of divergence between the two articles are two elements that define the nature of the question being asked. First of all, an important feature that needs to be taken into account when estimating a production function of skills is measurement error. [Cunha et al. \(2010\)](#) show that ignoring measurement error, either in the inputs or the output production function, can lead to biased estimates in the production function. This, together with the fact that a latent factor structure can be interpreted as unobserved

heterogeneity (Carneiro, Hansen, & Heckman, 2003), thus potentially improving the accuracy of the estimates, has made factor analysis a popular tool to get accurate estimates of the production function of skills (Cunha et al., 2010; Cunha & Heckman, 2008; J. J. Heckman, Stixrud, & Urzua, 2006). This article is the first one to estimate production function of skills via a latent-factor approach, nested within a model of household behavior.

Additionally, a major point in which this article departs from the analysis of Del Boca et al. (2014) is given by the fact that I estimate a collective model of household behavior, allowing parents to have different preferences, as opposed to using the unitary approach. The unitary framework has several empirical implications that have been rejected in various contexts. One of such is the income pooling assumption: the fact that when making a transfer to the household, the identity of the recipient will have no consequences in the observed outcomes. In particular, it has been found that cash in the hands of women translate into better child outcomes than cash in the hands of men in various contexts such as South Africa (Duflo, 2000), Mexico (Attanasio & Lechene, 2014) Brazil, the US and Ghana (Thomas, 1994). Given that most monetary transfer programs have the mother as being the recipient of such benefits, considering a collective model of household behavior allows us to identify to what extent it is justified to spend additional resources in targeting a particular household member as the recipient. This is an salient features of such programs that cannot be captured in a unitary framework. Additionally, the empirical regularity that women empowerment and child development are positively correlated (Haddad, Hoddinott, Alderman, et al., 1997), cannot be explained by considering the household as a single entity with one utility function. The collective model of household behavior has been proved to be a good alternative to the unitary approach that is able to explain the aforementioned facts.

This article also makes methodological contributions to the literature on Family Economics and Labor Economics. First of all, there are very few empirical applications of the collective model of household behavior and this article proposes a novel identification strategy for such models. The few empirical applications of the collective model use information on the consumption of private goods in order to assess the relative importance of each household member in the process of decision-making. The crucial assumption is that there is reliable information available on the consumption of purely private goods<sup>4</sup>. By having information about measures of empowerment and gender roles within the household, I do not need to impose such assumptions and I am able to use direct information on the process of decision-making -allowing for measurement error- in order to identify the bargaining power of each member of the household.

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<sup>4</sup>Perhaps the most common private good used for this purpose is clothing. However, the assumption that each spouse is indifferent about the clothing of the other seems problematic.

Moreover, this article is the first- to the best of my knowledge- using particle filtering techniques in the context of estimating a model of household behavior. Particle filtering techniques are often used in macroeconomics and macro econometrics in order to estimate non-linear non-gaussian factor models (Fernández-Villaverde & Rubio-Ramírez, 2007). Although such techniques are computationally expensive, they allow better empirical estimates by imposing fewer assumptions compared to alternatives such as the Extended Kalman Filter. This article is the first one to use such techniques in the context of family economics and one of the few applications in applied microeconomics. As such, it brings to the table a new methodology for the estimation of such models. Finally, an additional contribution of this paper is to bring the literature of estimating a production function of skills in the context of a developing country, which is the case of Chile. The conditions under which families live in developed and developing countries are different and it is hard to extrapolate the results from one to the other. Additionally, in the behavioral model we can take into account various challenges of greater importance in developing countries, such as female labor force participation, and take into account the effect that policy counterfactuals can have in such.

An important feature regarding the process of skills formation in young children is that mothers tend to invest significantly more time in their children than fathers. One possible explanation for this is that mother's time is more productive than father's time. Additionally, it can be due to differences in preferences or to a relative disempowerment of women with respect to men. We cannot assess the extent to which each factor contributes to the overall difference between fathers and mother by using a unitary model of household decision-making. By estimating a collective model of household behavior I am able to disentangle the contribution of each factor to the total difference in time invested between parents. I find that 14% of such difference is due to women being relatively less empowered than men in the average household and the remainder is explained by differences in preferences. I find no evidence of mother's time being more productive than father's time in the production of skills.

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

## 2 Review of the literature

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

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

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

Although [Del Boca et al. \(2014\)](#) brings to the literature the consideration of fathers and mothers altogether in the production of cognitive skills in children, it does so in a unitary approach. Their modeling approach fails to incorporate the fact that parents might have differences in preferences. It is important to take into account this fact as cash transfers are an important policy tool to alleviate poverty in developing countries and most of these programs explicitly state that the recipient of such transfers should be the mother. When making a transfer to a mother, not

only the resources of the household will increase but the decisions of the household will be more aligned with preferences of the mother. The unitary approach fails to take into account this second effect which the literature has acknowledged to be significant <sup>5</sup>. Additionally, [Del Boca et al. \(2014\)](#) do not observe monetary investments in children. The identification of this item comes exclusively from assuming a particular functional form of the utility and the production functions. The authors do not incorporate childcare decisions in their model nor the possibility of some degree of inheritance in the production of skills or of unobserved heterogeneity. The authors rely on using one test score as a measure of skills. This limitation will be addressed in the current paper given that the dataset used contains multiple measures for both, inputs and outputs. With this, I am able to allow for measurement error in this variables and also take into account a very important feature in the production of skills. That is, when analyzing the time that parents spend with their children, not only the amount but the quality matters ([Hanushek, 1992](#)). By observing the frequency with which parents perform different types of activities with their children I am able to control for this fact.

The second area of the literature to which this article is related is to the empirical implementation of collective models of household behavior. The income pooling assumption has been rejected in contexts as diverse as Sweden ([Cesarini, Lindqvist, Notowidigdo, & Ostling, 2013](#)), South Africa ([Duflo, 2000](#)), Mexico ([Attanasio & Lechene, 2014](#)) Brazil, the US and Ghana ([Thomas, 1994](#)). This has motivated a significant amount of research towards exploring alternatives such as the collective model of household behavior. In the collective model of household behavior agents are allowed to have different preferences. However, often invoking folk theorem arguments as the nature of interactions within the family is repeated, it is assumed that the results of the decisions within families are Pareto Optimal. Some of the main theoretical characteristics of the collective model of household behavior are developed in [Blundell, Chiappori, and Meghir \(2005\)](#).

Although some of the main properties of the collective model of household behavior have been explored, there are still very few empirical implementations of such model, one exception being [Cherchye, De Rock, and Vermeulen \(2012\)](#). In their model, the authors assume that each parent has his or her own preferences and each parent derives utility from the time they spend with their children. By following such an approach, they ignore the fact that the amount of time parents spend on their children might have an impact on their skills. This present article contributes to the literature related to the collective model of the household by being the first one to rationalize such model of household behavior taking into account the production of skills in children.

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<sup>5</sup>See for instance [Attanasio and Lechene \(2014\)](#) and [Bobonis \(2009\)](#)



Additionally, this article provides a new framework for identifying collective models of household behavior. The usual identification strategy of such models relies on observing the consumption of a given number of private goods, clothing being the most popular choice. Once the decisions of consumption of such private goods are observed, there is a one to one mapping from these decisions into the Pareto weight given to each agent. However, such arguments deny the fact that every good consumed within the household has a public component, as it is reasonable to assume that couples care about each other's clothing, for example. In this article I will improve upon such estimation strategies in two points by using a novel component of the dataset which includes elements of women empowerment within the household. In order to get an idea of where in the Pareto frontier a family is located I will use a set of questions related to female-male empowerment within the household and gender roles, rather than private consumption.

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

The finding that transfers made to women translate into better child outcomes still deserves some analysis from the literature. Although one valid interpretation is that women are expected to spend their own income on public goods within the household, as explained by Bobonis (2009), or to the fact that they simply have stronger preferences for child outcomes than men, there are multiple possible explanations. Blundell et al. (2005) show that as long as the marginal willingness to pay for child outcomes is higher for women than for men we will have such a result. However, having women with stronger preferences for child outcomes is not a necessary condition for such statement. Similarly, Basu (2006) provides an example where even in the case in which women care more for their children, there might be an inverted-U relationship between the bargaining



power of the women and the welfare of children as once women become relatively more powerful they can devote all the resources derived from child labor into their own private consumption. All this shows that it is important for the design of policies to understand which is the mechanism generating the positive relationship between women empowerment and child outcomes. In this article I explicitly allow parents to have different preferences for children and by estimating the structural parameters of the model I can analyze which mechanisms generate such relationship.

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

Additionally, this is one of the few articles that have attempted to estimate a production function of skills in a developing country. Much attention has been focused on the United States and Europe due to the availability of data. For the purpose of this article I will use a unique dataset from Chile that will bring the estimation of production of skills into a new context. A final contribution of this paper relies on the estimation strategy. Estimating dynamic models with continuous state variables is a huge challenge in microeconomics. Different solutions such as discretization ([Keane, Todd, & Wolpin, 2011](#)) have been proposed. I bring to the table a new alternative commonly used in macroeconomics and macro econometrics: particle filtering techniques.

### 3 Data and Preliminary Evidence

I will use a rich longitudinal dataset from Chile. Chile is the country of Latin America with the highest GDP per capita - \$US 20,000 PPP- and is often considered a case of economic success in the region due to the good economic performance during the last twenty years. Two of the most distinctive facts about 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 developed economies but also with similar countries in terms of income and geographic location.

The dataset used for this project comes from the Early Childhood Longitudinal Survey from Chile (ECLS). The first wave of this survey was collected in 2010 and includes a nationally representative sample of all households in Chile with a child under 5 years of age, which accounts for 15,000 households. The second wave was implemented in 2012 and included 85% of the households in the original sample and 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.

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

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

The dataset includes multiple test scores solved by the children and questionnaires answered

by the primary caregiver of the child in order to assess the skills level of children, for different domains such as socio-emotional development, behavioral problems and development of vocabulary. Unfortunately, not every test was answered by all the children as all of them include different age specifications<sup>6</sup>. The description of the tests included in the sample is included in Tables 1 and 2. These test scores will be considered a noisy signal of the true level of skills for children.

I drop from the sample those families that do not satisfy these criteria and those that did not complete all the tests performed in order to assess the skills level of their children. The description of how the sample is selected is described in Table 3. The sample considered for the analysis consists of 950 families. Some descriptive statistics of the sample used, for the 2012 wave, are included in Table 4 and some details about the age distribution of the children included, for the 2012 wave, are included in Table 5.

We see that fathers, whose average age is 37, are on average three years older than mothers, whose average age is 34. There is not much difference in terms of schooling as both fathers and mothers attain on average 11 grades of education. We do observe significant differences between fathers and mothers in labor market variables. Fathers participate in the labor force on average 43 hours a week, which is almost twice the average of mothers at 24 hours. As will be mentioned in the preliminary evidence section, unemployment does not explain a great deal of the low levels of hours that mothers participate in the labor market. It is rather due to women being actively out of the labor force, not looking for a job but rather reporting that they don't work because they have to take care of their children.

When comparing fathers who work and mothers who work, we observe a dramatic difference in the wages earned by both. Fathers earn \$75,800 Chilean Pesos on average whereas the weekly wage for mothers is \$49,320 Chilean Pesos<sup>7</sup>. In terms of ages of children, we see that the sample includes a somewhat homogeneous group as the average age is five years old, the oldest one being six and the youngest one being four.

The survey also reports the frequency with which parents perform different types of activities with their children. The description of each of these activities is presented in Tables 6 and 7. In Figure 1 I present the average frequency for each activity that parents report performing with the child for the activities reported in 2012. As can be seen, in every activity fathers report a lower frequency than mothers. The most common activities that parents perform with their children is

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<sup>6</sup>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.

<sup>7</sup>The exchange rate for 2012 corresponds to \$1 Chilean peso for \$0.002 USD

sharing a meal, talking to them and teaching them the numbers or letters. The most less common activities are taking the children to cultural activities, parks or reading to them.

A novel feature of this dataset is the inclusion of questions regarding female empowerment and gender roles within the household. For instance, there is information on whether it is the mother or the father who administers the income and whether the mother considers that it is better to have a bad marriage than to remain single. These variables allow us to identify to what extent the woman has a saying in the household and if she has some power at all when making the decisions of economic relevance. The variables used to assess the degree of women empowerment in the household are presented in Table 11. Tables 15 and 16 include summary statistics of the answers provided about the empowerment questionnaires. It is interesting to see, for instance, that 64% of men think that women should devote all their time to taking care of children and should work only in the case there is remaining time. However, as noted in Table 16 women also consider that they should be more in charge of children than working, as for instance the question related to “A woman in charge of chores should not work” receives an average score of 2.61 out of 4. These facts show that female empowerment should be an important concern for policymakers in this subpopulation.

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 12.

A relevant input into the production of skills is the amount of monetary investments that parents make in their children. These type of investments can be considered as any type of materials that can improve the living conditions of children or that can stimulate the learning experiences of children such as toys, food investments, physical space exclusively used by the child, and so on. Previous studies such as [Del Boca et al. \(2014\)](#) and [Bernal \(2008\)](#) take into account such factors into the production of skills in children but do not observe such measures of investments. The identification of how monetary investments affect the production of skills in children in their studies relies then on functional forms assumption. Contrary to previous cases in the literature, I will use some indicators of parental investments in children that will give some idea of how parents invest in their children. Some of these measures are exactly the same as used in [Cunha et al. \(2010\)](#), which come from the HOME inventory test score. The details of the measures used to assess the level of monetary investment in the children can be found in Tables 13 and 14.

## 4 Preliminary Evidence

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

### 4.1 Gaps in skills emerge early in life

When analyzing height at birth, weight at birth and the incidence of pre-term births<sup>8</sup>, for different income groups, we do not observe huge differences between poor and rich children, as can be seen in Figure 2. However, we do observe differences in various dimensions of development such as vocabulary, communication skills, motor skills and cognitive achievement, when children are five years olds. This can be seen in Figure 3. The figure reports the standard deviations below/above the mean for each income group. We see, for instance, that children in the lowest income quintile score 0.1 standard deviations below the mean in the Battelle test score for Motor Skills whereas children in the richest quintile score 0.15 standard deviations above the mean. The most dramatic case is vocabulary, where children in the lowest income quintile score 50% of a standard deviation below children located in the richest income quintile. This early emergence of gaps in the development of children is consistent with the literature (Schady et al., 2015; Cunha et al., 2010) and because of this interventions aimed at improving skills of people should focus on early childhood.

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

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

The fact that unemployment plays a small role in explaining the low levels of female activity in

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

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

### **4.3 Mothers spend more time with children than fathers**

As shown previously in Figure 1, mothers spend more time with their children, in every activity, than fathers do. One possible explanation for this factor is given by the labor supply differences. Fathers specialize in remunerated activities in the labor market whereas mothers do so taking care of children. Indeed there is a negative correlation between time investments and labor supply decisions for both fathers and mothers, in the two waves of the dataset being used, as can be seen in Tables 17 and 18.

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

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

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

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

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

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

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



## 5 Economic Model

In this section I will describe the economic model used to rationalize investments in children altogether with household behavior. Each household ( $h$ ) is composed of two agents ( $j$ ); namely the father ( $f$ ) and the mother ( $m$ ). In each household there is also a child with a level of skills denoted by ( $s$ ) who is not a decision maker<sup>9</sup>. 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 whether or not to participate in labor market ( $h_t^j$ ). Additionally, during the first period parents need to decide if the child attends preschool services or not ( $a_t$ ). There is a preference shock  $\epsilon_t$  associated with each decision of labor supply and preschool service. As there are two decisions of labor supply and two possible of preschool services this shock is four-dimensional. In particular, the choice set for labor supply and childcare decisions is given by  $D_t = \{(h_t, a_t) : h_t \in \{0, 1\}, a_t \in \{0, 1\}\}$ .  $q_t^{j,d}$  is an indicator function for individual  $j$  in period  $t$  taking the value of 1 if decision  $d \in D_t$  is taken and 0 otherwise. I assume the preference shock follows a multivariate normal distribution with mean zero and variance  $\Omega$ . The flow utility derived for each parent  $j$  in time  $t$  is given by the following utility function:

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

where  $\epsilon_{d,t}^j$  is the  $d$ -th element of the vector  $\epsilon_t$

At period  $t$  the skills of the child are produced by monetary investments  $I_t$ , time investments from both parents ( $e_t^j$ ), preschool attendance ( $a_t$ ), the ability of the primary caregiver of the child ( $PG$ ) that is constant over time, the previous level of skills  $s_{t-1}$  and the age of the child in months ( $\tau_t$ ). I allow for unobserved heterogeneity in the production of skills denoted by ( $\eta_{s,t}$ ). The variable  $Members_t$  denotes the number of household members present in period  $t$  in the household. The idea is to capture that by having additional household members not only the production of skills might be affected but also the productivity of each input. The production of skills is specified in the following equation:

$$s_t = r_t s_{t-1}^{\theta_0} \tilde{I}_t^{\theta_1} \tilde{e}_t^{\theta_2} \quad (2)$$

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

where  $r_t$  denotes the total factor productivity specified as:

$$r_t = \exp(\delta_0 + \delta_1 \tau_t + \delta_2 a_t + \delta_{3,t} PG + \delta_4 \text{Members}_t + \eta_{st}) \quad (3)$$

$\tilde{e}_t$  is the total time effort invested in the child given by the production function:

$$\tilde{e}_t = \left[ \gamma_0 \left( \tilde{e}_t^f \right)^\phi + \gamma_1 \left( \tilde{e}_t^m \right)^\phi \right]^{1/\phi} \quad (4)$$

where

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

and

$$\tilde{I}_t = I_t \exp(\eta_{I_t}) \quad (6)$$

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

## 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 different set of incentives in the process of skills production. Parents face a different set of incentives given that children start the formal schooling years and children start behaving more as an agent making their own decisions that might have consequences in their own skills. For this reason, I only model childhood lasting for two periods: birth to age 3 and age 3 to age 5. This is exactly the same assumption made as in [Del Boca et al. \(2014\)](#). The problem of the household in the second period

is given by:

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

$\Psi_2$ , 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 subject to the technological constraint given in 2, to the time constraint for each agent:

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

and to the budget constraint

$$c_2^f + c_2^m + I_2 = Y_2^f + Y_2^m + w_2^m h_2^f + w_2^f h_2^m + \Xi_2 \quad (9)$$

where  $w_2^j$  represents the wage offer for individual  $j$ ,  $Y^j$  is the corresponding non-labor income and  $\Xi_2$  is the total non-labor income that cannot be attributed to any specific household member. Examples of elements included in the  $\Xi_2$  term are subsidies for water consumption for the household. Note that in the second period parents don't make decisions regarding childcare attendance as virtually every child in the sample goes to preschool during the second period.

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

$$V_1(\Psi_1) = \max_{\{I_1, \{c_1^j, e_1^j, h_1^j\}_{j=m,f}\}} \mu_1 u_1^f(c_1^f, h_1^f, e_1^f, d_1^f, s_1) + (1 - \mu_1) u_1^m(c_1^m, h_1^m, e_1^m, d_1^m, s_1) + \beta \mathbb{E} [V_2(\Psi_2)] \quad (10)$$

I assume that wages are following a Mincer equation:

$$\ln(w_t^j) = \beta_0^j + \beta_1^j yrschool_t^j + \beta_2^j age_t^j + \beta_3^j (age_t^j)^2 + \varepsilon_{t,w}^j \quad (11)$$

where  $\varepsilon_{t,w}^j \sim N(0, \varepsilon_{w_j})$  is measurement error<sup>10</sup>. Additionally, the relative importance of each household member will depend on characteristics of the household. In particular, I assume the

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<sup>10</sup>Note that I am imposing a separate distribution for men and women. We could assume that all the correlation is yet given by assortative mating and is no necessity to assume a bivariate distribution in their wages. The only difference will be to estimate an additional parameter which will be the correlation between wage offers

following parametrization of  $\mu_t$ :

$$\mu_t(X_t) = \underline{\mu} + \bar{\mu} \left( \frac{\exp(\Lambda' X_t + \eta_{\mu t})}{1 + \exp(\Lambda' X_t + \eta_{\mu t})} \right) \quad (12)$$

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 <sup>11</sup>. In the  $X$  variables I include the ratio of offered wages, the difference of ages between spouses, the difference in grades of schooling and the father's share in non labor income. Additionally, I include conditions of the local labor market that include the relationship between male and female unemployment, the sex ratio and the wage ratio in the region of residence of the household. Similar specifications to this one have been used previously in the literature <sup>12</sup>. I also include the term  $D$  which is the distance from the household to the nearest women protection center. There is at least one women protection center in every region in Chile. These centers offer legal and counseling services to women who are not in a stable relationship with their spouse. The key idea, in this case, is that the distance to the center affects the bargaining power of the household but does not alter the process of decision-making in other respects.

$$X = \left[ \frac{w^f}{w^m}, \frac{Y^f}{Y^f + Y^m}, age^f - age^m, yrschool^f - yrschool^m, \frac{Women}{Men}, \frac{U^{Men}}{U^{Women}}, \frac{w^{Men}}{w^{Women}}, D \right] \quad (13)$$

where  $\bar{U}$  denotes the unemployment rate for each gender  $\frac{Female}{Male}$  is the sex ratio in the region of residence of the household, and  $\frac{w^{male}}{w^{female}}$  is the wage ratio between women and men in the region of residence. These variables are what the literature refers to as distribution factors, variables that affect the behavior of the household only through its direct impact on the bargaining power. Descriptive statistics of these variables can be found in Table 22.

The state variables are given by:

$$\Psi_t = \{r_t, s_{t-1}, \boldsymbol{\eta}_t, \Xi_t, X_t, \{\epsilon_{d,t}^j, Y_t^j, w_t^j\}_{j=m,f}\} \quad (14)$$

<sup>11</sup>The assumption that  $\mu$  is bounded given by  $\mu \in [\underline{\mu}, \bar{\mu}] \subseteq [0, 1]$  is made without loss of generality.

<sup>12</sup>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 the vector  $\boldsymbol{\eta}_t$  collects the unobserved heterogeneity:

$$\boldsymbol{\eta}_t = \{\eta_{I_t}, \eta_{e_t^f}, \eta_{e_t^m}, \eta_{\mu_t}, \eta_{s_t}\} \quad (15)$$

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

## 5.2 Model solution

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

$$e_2^{m,*} = \frac{\kappa_2^2(\mu_2)\theta_2\gamma_1}{(1-\mu)\alpha_{4,2}^m(1+h_2^m)} \xi_2(m) \exp(-\eta_{e_2^m}) \quad (16)$$

$$e_2^{f,*} = \frac{\kappa_2^2(\mu_2)\theta_2\gamma_0}{\mu\alpha_{4,2}^f(1+h_2^f)} \xi_2(f) \exp(-\eta_{e_2^f}) \quad (17)$$

$$I_2^* = \frac{\kappa_2^2(\mu_2)\theta_1 \left( h_2^f w_2^f + h_2^m w_2^m + Y_2^f + Y_2^m + \Xi \right)}{\kappa_2^1(\mu_2) + \kappa_2^2(\mu_2)\theta_1 P_I} \exp(-\eta_{I_2}) \quad (18)$$

$$c_2^{f,*} = \max\left\{ \frac{\alpha_{1,2}^f \mu_2 I_2}{\theta_1 \kappa_2^2(\mu)}, \zeta \right\} \quad (19)$$

$$c_2^{m,*} = \max\left\{ \frac{\alpha_{1,2}^f \mu_2 I_2}{\theta_1 \kappa_2^2(\mu)}, \zeta \right\} \quad (20)$$

$$e_1^{m,*} = \frac{[\kappa_2^2(\mu_2)\theta_2 + \beta\kappa_2^2(\mu_2)\theta_2\theta_0] \gamma_1}{(1-\mu)\alpha_{4,2}^m(1+h_2^m)} \xi_1(m) \exp(-\eta_{e_1^m}) \quad (21)$$

$$e_1^{f,*} = \frac{[\kappa_1^2(\mu_1)\theta_2 + \beta\kappa_2^2(\mu_2)\theta_2\theta_0] \gamma_0}{\mu\alpha_{4,2}^f(1+h_2^f)} \xi_1(f) \exp(-\eta_{e_1^f}) \quad (22)$$

$$I_1^* = \frac{[\kappa_1^2(\mu_1)\theta_1 + \kappa_2^2(\mu_2)\theta_0\theta_1\beta] \left( h_2^f w_2^f + h_2^m w_2^m + Y_2^f + Y_2^m + \Xi - P_a a \right)}{\kappa_1^1(\mu_1) + \kappa_1^2(\mu_1)\theta_1 + \beta\theta_0\theta_1\kappa_2^1(\mu_2)} \exp(-\eta_{I_1}) \quad (23)$$

$$c_1^{f,*} = \max\left\{ \frac{\alpha_{1,2}^f \mu_2 I_2}{\theta_1 \kappa_1^2(\mu_1) + \beta\theta_0\theta_1\kappa_2^2(\mu_2)}, \zeta \right\} \quad (24)$$

$$c_1^{m,*} = \max\left\{ \frac{\alpha_{1,2}^f \mu_2 I_2}{\theta_1 \kappa_1^2(\mu_1) + \beta\theta_0\theta_1\kappa_2^2(\mu_2)}, \zeta \right\} \quad (25)$$

where

$$\xi_t(j) = \frac{\left(\gamma_j \mu \alpha_{4,t}^f (1 + h_t^f)\right)^{\frac{\phi}{1-\phi}}}{\gamma_0 \left[\gamma_0 (1 - \mu) \alpha_{4,t}^m (1 + h_t^m)\right]^{\frac{\phi}{1-\phi}} + \gamma_1 \left[\gamma_1 \mu \alpha_{4,t}^f (1 + h_t^f)\right]^{\frac{\phi}{1-\phi}}} \quad (26)$$

$$\kappa_t^i(\mu) = \mu \alpha_{i,t}^f + (1 - \mu) \alpha_{i,t}^m \quad (27)$$

$$\zeta = 1.0e - 5 \quad (28)$$

and

$$\gamma_j = \begin{cases} \gamma_0 & \text{if } j = f \\ \gamma_1 & \text{if } j = m \end{cases} \quad (29)$$

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

$$\begin{aligned} (h_2^{f,*}, h_2^{m,*}) = \max_{\{h_2^f, h_2^m\}} & \mu_2 u_2^f(c_2^{f,*}(h_2^f, h_2^m), h_2^f, e_2^{f,*}(h_2^f, h_2^m), d_2^f(h_2^f, h_2^m), s_2(h_2^f, h_2^m)) + \\ & (1 - \mu_2) u_2^m(c_2^m(h_2^f, h_2^m), h_2^m(h_2^f, h_2^m), e_2^{m,*}(h_2^f, h_2^m), d_2^m(h_2^f, h_2^m), s_2(h_2^f, h_2^m)) \end{aligned} \quad (30)$$

$$\begin{aligned} (h_1^{f,*}, h_1^{m,*}, a) = \max_{\{h_1^f, h_1^m, a\}} & \mu_1 u_1^f(c_1^{f,*}(h_1^f, h_1^m, a), h_1^f, e_1^{f,*}(h_1^f, h_1^m, a), d_1^f(h_1^f, h_1^m, a), s_1(h_1^f, h_1^m, a)) + \\ & (1 - \mu_1) u_1^m(c_1^m(h_1^f, h_1^m, a), h_1^m(h_1^f, h_1^m, a), e_1^{m,*}(h_1^f, h_1^m, a), d_1^m(h_1^f, h_1^m, a), s_1(h_1^f, h_1^m, a)) \\ & + \beta \left[ V_2(\Psi_2(h_1^f, h_1^m, a)) \right] \end{aligned} \quad (31)$$

### 5.3 Inefficiency in Child Investments and Female Empowerment

As shown in the preliminary evidence, women spend more time with their children even when controlling for labor supplies. This, altogether 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, there are different possible explanations why women spend more time with their children than men.

First of all, women's time might be more productive in enhancing skills of children than men's time. If it were the case, the optimal allocation of time in the household would be for women to spend more time with their children without invoking any preferences-based argument. However, in addition to this argument, the relative empowerment of each member might be a plausible explanation. Given that both parents are making investments in a public good (skills of children) and that effort is costly and privately exerted, the fact that women spend more time with children might be a consequence of their relative disempowerment in the household rather than having different preferences in terms of child development<sup>13</sup>.

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

Consider the centralized problem of choosing the effort levels for the second period in order to maximize the skills of children -taking all other inputs as fixed- subject to the fact that the total amount of effort exerted should not exceed the total amount of effort found in the problem of the household described in 16-17. We are basically asking whether or not it is possible to find an alternative allocation of time that would make children better off, without modifying the total amount of effort exerted by both parents. The problem is formally defined as:

$$\max_{e^f, e^m} s_2(e^f, e^m, \cdot) \text{ subject to } e^f + e^m = e^{f,*} + e^{m,*} \quad (32)$$

Define the solution to the problem in 32 as  $(e^{f,c_1}, e^{m,c_1})$ .

Similarly, we can define an alternate centralized problem where we maximize skills subject to

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<sup>13</sup>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.

the fact that the total time-cost exerted into the production of skills should not exceed that found in the household's problem defined in 1-15. Formally:

$$\max_{e^f, e^m} s_2(e^f, e^m, \cdot) \text{ subject to } c(e^f) + c(e^m) = c(e^{f,*}) + c(e^{m,*}) \quad (33)$$

Where the cost of effort is given by  $c^j(e^j) = \alpha_{4,2}^j e^j (1 + h^j)$ . We will call the solution to 33 as  $(e^{f,c_2}, e^{m,c_2})$ . In both cases, for  $l = 1, 2$ , we do find that:

$$\frac{\left(\frac{e^{f,c_l}}{e^{m,c_l}}\right)}{\left(\frac{e^{f,*}}{e^{m,*}}\right)} \propto \left[\frac{(1-\mu)}{\mu}\right]^{\phi/(1-\phi)} \quad (34)$$

The difference of ratios of effort in the centralized solutions and in the household problem originally defined in 1-15 depends on the Pareto weight and the degree of substitutability between parental efforts. When the Pareto weight heavily favors one member, and if there is some degree of substitutability between parental effort, there would be an inefficient allocation in time investments given that we can find an alternative allocation with the same amount of cost, or the same amount of total effort, that will yield better child outcomes.

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

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

## 6 Estimation

The unobserved latent variables in the model are given by:

$$K = \{\{\ln(s_t), \ln(\hat{e}_t^f), \ln(\hat{e}_t^m), \ln(\hat{I}_t), \mu\}_{t=1,2}, \ln(PG), \ln(s_0)\} \quad (35)$$

and are not observed perfectly. 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:

$$Z_m^k = \iota_{m,0}^k + \iota_{m,1}^k k + \varepsilon_m^k \text{ for } m = 1 \dots N_k \quad (36)$$

where  $Z_m^k$  denotes the measure  $m$  for the latent variable  $k$  and  $N_k$  denotes the number of measures available for the latent factor  $k$ . The variables used as measurements for each factor are described in Tables 6 - 13. We assume the  $\varepsilon_m^k$  are uncorrelated across observations and follow a distribution  $\mathcal{N}(0, \sigma_{km})$

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

$$P(O|X; \Theta) = \mathcal{L}(\Theta|O; X) \quad (37)$$

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

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

for  $t=1,2$ :

$$\begin{aligned} O_t &= \{h_t^f, h_t^m, a_t, Z_t\} \cup \underbrace{\{w_t^f\}}_{\text{if } h_t^f > 0} \cup \underbrace{\{w_t^m\}}_{\text{if } h_t^m > 0} \\ Z_1 &= \{\ln(s_1), \ln(\hat{e}_1^f), \ln(\hat{e}_1^m), \ln(\hat{I}_1)\} \\ Z_2 &= \{\ln(s_2), \ln(\hat{e}_2^f), \ln(\hat{e}_2^m), \ln(\hat{I}_2), \mu_2\} \end{aligned} \quad (38)$$

Note that we only have measures of  $\mu_2$  available for the second period. We thus need to integrate over the distribution of the bargaining power in the first period. The exogenous characteristics are given by the age, grades of schooling, age of parents and the distribution factors in  $X$ .

Given that we need to integrate over the the distribution of the unobserved factors as they

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

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

## 6.1 Identification

The identification argument is divided in three parts. First, I show how the parameters of the measurement system described in 36 are identified. Secondly, I show what variation in the data allows us to recover the distribution of the latent factors. Finally, I show how the parameters of the economic model are recovered.

### 6.1.1 Measurement System

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

$$Z = \iota_0 + \iota_1 K + \varepsilon \quad (39)$$

where  $Z \in \mathbb{R}^M$  contains all the measures available,  $M$  is the total number of measurements for all the factors,  $K \in \mathbb{R}^{11}$  is the vector of 11 factors and  $\varepsilon \in \mathbb{R}^M$  is measurement error.  $\iota_1 \in \mathbb{R}^{M \times 11}$  is the matrix of factor loadings. We normalize  $E[k] = 0$  for each factor. This normalization is irrelevant given that we can re-define new measures  $Z - \iota_0$  and the analysis will remain unchanged. From the observed measures  $Z$  we can obtain the covariances by noting that:

$$\Sigma_Z = \iota_1 \Sigma_K \iota_1' + \Sigma_\varepsilon \quad (40)$$

where  $\sigma_x$  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  $\Sigma_k$  and  $M \times (M + 1)/2$  elements in  $\Sigma_\varepsilon$ . 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 fact that we have a dedicated measurement system reduces the parameters to estimate in the  $\iota_1$  matrix to only  $M$ . Additionally, we can impose the normalization of one factor loading into each factor as is usual in factor models. That is, the first measure used for each factor will have a factor loading normalized to one. This 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  $\varepsilon_m^{\ln(s_0)} \perp \varepsilon_{m'}^{k'}$  for  $m = 1 \dots N_{\ln(s_0)}$ ,  $k \neq \ln(s_0)$ ,  $m' = 1 \dots N_k$ . The details of why this is enough to identify the parameters in the measurement system are described in Appendix 11.1.

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

$$\frac{Cov(Z_m^k, Z_1^{\ln(s_0)})}{Cov(Z_1^k, Z_1^{\ln(s_0)})} = \iota_{m,1}^k \quad (41)$$

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

$$\frac{Cov(Z_m^{\ln(s_0)}, Z_1^k)}{Cov(Z_1^{\ln(s_0)}, Z_1^k)} = \iota_{m,1}^{\ln(s_0)} \quad (42)$$

### 6.1.2 Distribution of unobserved factors

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

$$ME_j = \left\{ \frac{Z_j^k}{\iota_{j,1}^k} \right\}_{k \in K} \quad (43)$$

$$me_i = \left\{ \frac{\varepsilon_j^k}{\iota_{j,1}^k} \right\}_{k \in K} \quad (44)$$

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

$$E[me_1|K, me_2] = 0 \quad (45)$$

$$me_2 \perp\!\!\!\perp \theta \quad (46)$$

we can use Theorem 1 in [Schennach \(2004\)](#) in order to non-parametrically identify the distribution of 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:

$$p(K) = \frac{\int_{-\infty}^{\infty} e^{-i\chi K} e^{\left( \int_0^{\chi} \frac{E[iME_1 e^{i\psi ME_2}]}{[e^{i\psi ME_2}]} d\psi \right)} d\chi}{2\pi} \quad (47)$$

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

$$Cov(Z_m^l, Z_{m'}^{k'}) = \iota_{m,1}^k \iota_{m',1}^{k'} Cov(k, k') + Cov(\varepsilon_m^k, \varepsilon_{m'}^{k'}) \quad (48)$$

### 6.1.3 Identifying the Production of skills

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

$$p\left(\ln(s_{t+1}) | \ln(s_t), \ln(\hat{e}_{t+1}^f), \ln(\hat{e}_{t+1}^m), \ln(\hat{I}_{t+1}), \mu, \ln(PG)\right) \quad (49)$$

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

$$s_{t+1} = f_s\left(s_t, \hat{e}_t^f, \hat{e}_t^m, \hat{I}_t^m\right) = E\left[\exp\left(\ln(s_{t+1}) | \ln(s_t), \ln(\hat{e}_{t+1}^f), \ln(\hat{e}_{t+1}^m), \ln(\hat{I}_{t+1}), \mu, \ln(PG)\right)\right] \quad (50)$$

where the expectation is taken with respect to the distribution in [49](#). However, note that we are interested in a function  $s_{t+1}$  that has as an additional argument the term  $\eta_{s_t}$  corresponding to heterogeneity. [Matzkin \(2007\)](#) has negative identification results in this case and shows that in order to be able to non-parametrically identify the function we are interested in, we need to

impose some restrictions. In particular, if we assume that the term  $\eta_{s_t}$  enters additively in 50 we can trivially identify the production of skills. Additionally, the distribution of  $\eta_s$  is identified as:

$$\begin{aligned}
& F_{\left(s_{t+1} | \ln(s_t), \ln(\hat{e}_t^f), \ln(\hat{e}_t^m), \ln(\hat{I}_t^m)\right)} \left( \tilde{s}_{t+1} | \ln(s_t), \ln(\hat{e}_t^f), \ln(\hat{e}_t^m), \ln(\hat{I}_t^m) \right) = \\
& P \left( s_{t+1} \leq \tilde{s}_{t+1} | \ln(s_t), \ln(\hat{e}_t^f), \ln(\hat{e}_t^m), \ln(\hat{I}_t^m) \right) = \\
& P \left( f_s \left( s_t, \hat{e}_t^f, \hat{e}_t^m, \hat{I}_t^m \right) + \eta_{s,t} \leq \tilde{s}_{t+1} | \ln(s_t), \ln(\hat{e}_t^f), \ln(\hat{e}_t^m), \ln(\hat{I}_t^m) \right) = \\
& P \left( \eta_{s,t} \leq \tilde{s}_{t+1} - f_s \left( s_t, \hat{e}_t^f, \hat{e}_t^m, \hat{I}_t^m \right) | \ln(s_t), \ln(\hat{e}_t^f), \ln(\hat{e}_t^m), \ln(\hat{I}_t^m) \right) \quad (51)
\end{aligned}$$

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 Parameters of the economic model

The parameters of the economic model are identified by a combination of exclusion restrictions, exogenous sources of variations and functional form specifications using some of the parameters already recovered from the distribution of the underlying factors.

For instance, it is not intuitive how to separately identify preferences for skills of child and price of childcare. I use as an exclusion restriction the distance to the nearest childcare service provider in order to be able to separately identify both components. The idea is that we can write the price of childcare as:

$$P_a = P_{a,0} + P_{a,1} \text{DChildcare} \quad (52)$$

where DChildcare is the distance from the household to the nearest childcare service provider. The key assumption is that the distance to childcare services affects the cost of such services but is not related to preferences for child development. I use the same exclusion restriction to identify the price of monetary investments in children. The idea is that the distance from households to the nearest childcare center is correlated with the supply of goods available for children in that neighborhood but is independent, conditional on the remaining factors, with respect to skills of children.

I also allow the price of monetary investments to change according to the availability of preschool



services in the neighborhood of residence of the household. I use the number of preschool institutions within a 5 kilometers radius of the household as an instrument for the supply of goods that could be used for enhancing skills in children. The idea is that households that have a larger number of such institutions in their surroundings, are more likely to see a larger supply of goods for children. Because of that, I allow the density of preschool institutions to alter the price of investments. The distribution of these variables, number of preschool institutions and the distance to the nearest preschool institution, can be found in Figure 5

In order to separately identify the parameters of the utility function of fathers and mothers we use common arguments used in the literature of collective models of household behavior (Chiappori & Donni, 2009). The use of distribution factors -variables that affect the behavior of the household but do not modify household behavior in any other way- allows us identify preferences for mothers and fathers. The main idea is that variation in such instruments will generate a movement along the Pareto frontier exclusively generated by the change in the bargaining power. The distribution factors used in this article have been previously used in the literature (Cherchye et al., 2012; Attanasio & Lechene, 2014; Blundell et al., 2005).

One additional identification issue to be mentioned is that of separately identifying preferences for skills in children and costs of exerting effort. We can rationalize a given amount of effort exerted from parents to children by a locus combinations of  $(\alpha_{t,2}^j, \alpha_{t,4}^j)$ . Rather than relying exclusively on functional form identification, I use information about additional family members contributing to household chores in order to obtain information about the cost of exerting effort into the children. The idea is that having an additional family member contributing to tasks such as cleaning the house shifts the cost of investing time in children.

Finally, the scheduling of monetary transfers to households is an additional source of identification. The central government gives monetary transfers to families in need, corresponding to approximately 40% of the households in Chile. In the case of the poorest households of the country, such transfers can represent 20% of the total income. The rules according to which such subsidies are given establish that households should have a score below a given threshold, for a score which is a composite measure of household material conditions and monetary income. Under the assumption that households just above the threshold and just below the threshold established for this transfer are similar, we observe a variation in the proportion of income earned by women that will give us some information about the preferences of mothers and fathers.

## 7 Results

The results of the parameters estimated, altogether with the corresponding standard errors are presented in Tables 23 - 31. The estimates of the measurement system are reported separately on Appendix 11.3 from Tables 41-49. As we see, childcare services tend to liberate more time resources from mothers than for fathers. In the same regard, having one additional member in the household decreases the cost of time investments more for mothers than for fathers.

Regarding the estimates of the production of skills, we see that there is no statistical difference in the productivity of time investments of mothers and fathers. It seems to be equally efficient for a child to spend one hour of productive time investment with her father or mother. It is not possible to make comparisons between the productivities of different inputs as they are measured in different units (except father's and mother's effort). Nonetheless, we see that monetary investments, childcare attendance, skills of primary caretaker and having adequate birth conditions all seem to have positive effects on the quality of a child.

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

The estimates of the measurement system are included in Tables 43 to 49. We can use these estimates in order to get an idea of which measures are more informative about the unobserved factors in the model. Every measure is contaminated by measurement error and with the estimation results we are able to extract the proportion of the variance due to true signal and the proportion due to noise.

$$\text{Signal-noise ratio}_{m,k} = \frac{\iota_{m,1}^2 \text{Var}(k)}{\iota_{m,1}^2 \text{Var}(k) + \text{Var}(\varepsilon_m^k)} \quad (53)$$

In Figures 15 to 24 I present the signal to noise ratio of parental investments. We find that cultural activities are the most informative about time investment in children and sharing a meal or performing household chores are within the group of less informative activities. We should be careful with the interpretation of these results: it does not mean that cultural activities are the most productive ones but rather they are the most informative ones. It can certainly be the case that there is an underlying activity that is not reported in the dataset that is performed more

often by those parents who perform cultural activities and it is the one that is really productive, not performing cultural activities by itself. Making inferences about which activities are more productive requires more analysis in this point.

### **7.1 Model fit**

The model does a good job when predicting labor force participation and childcare decisions of the household. In Figure 6 we observe that 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 age and female labor force is observed and we see this in Figure 7. There are no gradients related to education or age regarding male labor force participation as can be seen in Figure 8. The aggregates are reported in Tables 32 and 33. Similarly, I am able to replicate the demand for childcare services. In Figure 9 I show the predicted and observed demand for childcare services generated. The aggregates for demand of childcare services are reported in Table 34. The simulated patterns from the model are generated assuming shocks are at their means. Additionally, we can generate the simulated patterns drawing shocks from the corresponding distribution. The model fit corresponding to these simulations with 5,000 draws are reported in Figures 10 - 11. As we can see, in both cases the model fits well the data.

With the information about measures and the information from the production of skills, we can get a more precise estimate about the distribution of skills for each individual. The estimated smoothing distribution of skills, which uses all information available in order to make inference about the skills of each individual in sample, is estimated and the results are reported in Figure 12. The details for the construction of the smoothing distribution are presented in Appendix 11.5. The results confirm huge disparities in the skills between rich and poor kids.

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

In this section I describe the effects that different policy programs would have on the skills of young children. Additionally, I consider its effects on the female labor force participation and preschool attendance. The policies considered are: 1. doubling the amount of monetary transfers that poor households receive from the central government in the form of subsidies; 2. same as 1. but having father, rather than the mother, as the recipient of such transfers; 3. setting up a system

of free childcare services for children older than three and; 4. establishing a system of in-kind transferences where poor families receive goods that can be used to enhance the skills of young children such as books, toys and puzzles.

Cash transfers are a widely-used program in developing countries. Every country in Latin America has a form of cash transfer that varies by the amount given to the households, and the type of conditions that families need to fulfill in order to be beneficiaries (Fiszbein et al., 2009). Policymakers often invoke the effect of such programs on the promotion of skills of young children, as one of the many benefits of these policies. Moreover, the vast majority of these programs establish that for families with children, the mother should always be the beneficiary. The main argument for this being that cash in the hands of women is associated with better child outcomes than cash in the hands of men (Doepke & Tertilt, 2014).

Given the high use of cash transfers as a policy tool in developing countries, and given the explicit condition that transfers go to mothers rather than fathers or other adult members, the first counterfactual policy that I consider is to increase the amount of cash transfers given to mothers of young children. Since 2010, the value of transfers that poor families with children receive have increased significantly. Between 2012 and 2016, families in the lowest quintile of the income distribution, have seen an increase of 72.8%, in real terms, in the cash transfers that they receive from the central government. The details of these programs and how such increase was distributed between various policies are described in Appendix 11.7. Given that governments seem to spend every time more resources in these type of policies, the first counterfactual simulated in this paper consists on doubling the amount of monetary transfers that families located in the lowest quintile of the income distribution receive. Such policy would imply a transfer equivalent to 17.9% of the average income for families in the the lowest quintile, which corresponds to \$15,338 CLP a month.

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

Free childcare - preschool policies have also been very popular not only as a way to promote skills in young children but also as a tool to promote female employment. In 2013, the government of Chile established free and mandatory preschool services for children older than five years of age. In part because of that, Chile is now the country with the highest expenditure in preschool

education as a share of total government expenditure, of countries in the OECD <sup>14</sup>. Due to the increasing importance of such public policies, in the third counterfactual I simulate the effects of setting up free childcare services for children older than three years of age, coming from households 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 transfers programs are starting to become more popular in developing countries. In Chile, for example, such transfers are being done through the “Chile Crece Contigo”<sup>15</sup> (ChCC) program, established in 2009. ChCC is composed by a set of services for poor families with children younger than five years of age. The goal of the program is to guarantee that every child has the necessary resources so that they can achieve their full developmental potential during childhood. The program offers resources to parents such as a 24 hours phone line for inquiries about child development, the distribution of books, toys, songs and story books for children, as well as handling learning materials for parents in order to increase their knowledge about the process of child development. ChCC is the most important child development public program currently working in Chile. Due to 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 adequate for cognitive stimulation and music material to increase their vocabulary. In the fourth counterfactual I analyze the effects of spending the same amount of resources such as in counterfactual 1 -i.e. \$15,338 CLP a month per family- for families in the lowest income distribution, but doing it in the way of in-kind transfer.

The results of the counterfactuals can be seen in Tables 35-40. It is first important to note that cash in the hands of men or cash in the hands of women has virtually the same effect on every variable analyzed. With such transfers we observe a decrease in female and male labor force participation of less than 1%. The subsidized childcare increases female labor force participation in 0.74 but has no effect on male labor force participation. Additionally, in-kind transfers have no effect on the labor force participation of either parent.

The most important point to note regarding the results of the policy counterfactuals comes when analyzing the effects they have on the skills of children. As reported in table ?? monetary transfers do not close the gap in skills between rich and poor children. Initially, children in the richest quintile of the income distribution have, on average, skills above 1.02 standard deviation

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<sup>14</sup>Out of the total government expenditures, 2.3% go to the preschool system as opposed to the average of other OECD countries, which is 1.1% (Chile, 2013)

<sup>15</sup>Chile Grows with You, in Spanish

above children coming from the lowest quintile. Implementing monetary transfers to the father or the mother, virtually has no effect on this gap as such measure gets reduced only to one standard deviation. This can be explained by the fact that such transfers do not translate entirely to monetary investments in children, as can be seen in ???. The case of childcare subsidies is similar: the gap between rich and poor remains virtually the same. However, such policy implementation does not discourage labor force participation. Finally, it is important to note the relative effectiveness of in-kind transfers as a tool to close the gaps in skills between rich and poor. If we consider spending in monetary investments for children, one third of what is spent in monetary transfers to households, the gap between rich and poor is reduced by approximately 20%.

## 9 Conclusions

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

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

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

10    Figures and Tables

Table 1: 2010 Tests-Measures of child skills

Test	Description	Scoring Interpretation	Ages (in months)	Abbreviation
TEPSI	Psychomotor development test. Three areas of psychomotor development are included: coordination, language and gross motor development. A score including all these areas is also computed.	Higher score indicates a higher level of psychomotor development.	24-60	MS <sub>1,10</sub> -MS <sub>3,10</sub>
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 <sub>5,10</sub> -MS <sub>11,10</sub>

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 <sub>1,12</sub> -MS <sub>4,12</sub>
BATELLE	Batelle Instrument for Child Development. 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 <sub>5,12</sub> -MS <sub>10,12</sub>
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 <sub>13,12</sub>



Table 3: Description of sample used in the analysis

Number of households	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	4,718
Children with no weight or height at birth	4,125
Children with incomplete skills questionnaires	2,247
Households with incomplete questionnaires	950

Table 4: Summary statistics

Variable	Mean	(Std. Dev.)
Mother's age	34.52	(6.94)
Father's age	37.41	(7.96)
Mother's years of schooling	11.27	(2.97)
Father's years of schooling	10.72	(3.13)
Mother's hours of work (week)	24.22	(21.34)
Mother's hours of work (week)	43.2	(16.03)
Mother's wage (Weekly-Chilean Pesos thousands)	49.32	(79.59)
Father's wage (Weekly-Chilean pesos thousands)	75.88	(83.60)
Household's total Income (Weekly-Chilean pesos thousands)	124.55	(108.83)
Age of child (months)	64.59	(8.4)
N		950

Table 5: Age distribution (2012)

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

Table 6: Measures used for parental effort in 2012

Abbreviation	Activity
MS <sub>1<sub>EF,12</sub></sub>	Reads Children's storybooks or drawing books
MS <sub>2<sub>EF,12</sub></sub>	Tells her stories
MS <sub>3<sub>EF,12</sub></sub>	Sings to child
MS <sub>4<sub>EF,12</sub></sub>	Takes her to parks
MS <sub>5<sub>EF,12</sub></sub>	Takes her to museums, zoos, libraries or other cultural activities
MS <sub>6<sub>EF,12</sub></sub>	Spends time with her chatting or drawing
MS <sub>7<sub>EF,12</sub></sub>	Invites her to participate in household chores
MS <sub>8<sub>EF,12</sub></sub>	Takes her to the supermarket
MS <sub>9<sub>EF,12</sub></sub>	Shares a meal with her
MS <sub>10<sub>EF,12</sub></sub>	Teaches the animals and their sounds
MS <sub>11<sub>EF,12</sub></sub>	Teaches her the colors
MS <sub>12<sub>EF,12</sub></sub>	Goes with her to visit friends or family members
MS <sub>13<sub>EF,12</sub></sub>	Teaches her the numbers and how to count
MS <sub>14<sub>EF,12</sub></sub>	Teaches her words
For each question parents reply how often, during the last seven days, they perform each activity. The possible answers are: Never, 1-3 times, 4-6 times.	

Table 7: Measures used for parental effort in 2010

Abbreviation	Activity
MS <sub>1<sub>EF,10</sub></sub>	Reads Childre's storybooks or drawing books
MS <sub>2<sub>EF,10</sub></sub>	Tells her stories
MS <sub>3<sub>EF,10</sub></sub>	Sings to her
MS <sub>4<sub>EF,10</sub></sub>	Takes her to parks
MS <sub>5<sub>EF,10</sub></sub>	Takes her to museums, zoos, libraries or other cultural activities
MS <sub>6<sub>EF,10</sub></sub>	Plays with her
MS <sub>7<sub>EF,10</sub></sub>	Spends time with her talking or drawing

Table 8: Measures used for Skills in 2012

Abbreviation	Test
MS <sub>112</sub>	TADI-Cognitive subdomain
MS <sub>212</sub>	TADI-Motor skills subdomain
MS <sub>312</sub>	TEPSI-Motor skills subdomain
MS <sub>412</sub>	TADI-Language subdomain
MS <sub>512</sub>	Battelle-I
MS <sub>612</sub>	Battelle-II
MS <sub>712</sub>	Battelle-III
MS <sub>812</sub>	Battelle-IV
MS <sub>912</sub>	Battelle-V
MS <sub>1012</sub>	Battelle-T
MS <sub>1112</sub>	PPVT-Vocabulary Test

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

Table 9: Measures used for Skills in 2010

Abbreviation	Test
MS <sub>110</sub>	TEPSI-Coordination subdomain
MS <sub>210</sub>	TEPSI-Language subdomain
MS <sub>310</sub>	TEPSI-Motor skills subdomain
MS <sub>410</sub>	CBCL-Emotional intelligence
MS <sub>510</sub>	CBCL-anxiety -depression
MS <sub>610</sub>	CBCL-somatic complaints
MS <sub>710</sub>	CBCL-Isolation
MS <sub>810</sub>	CBCL-Sleeping disorder
MS <sub>910</sub>	CBCL-Attention deficit
MS <sub>1010</sub>	CBCL-Aggressive behavior

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

Table 10: Measures used for Skills of primary caregiver

Abbreviation	Test
MS <sub>1<sub>PG</sub></sub>	WAIS-Numerical test
MS <sub>2<sub>PG</sub></sub>	WAIS-Vocabulary test
MS <sub>3<sub>PG</sub></sub>	BFI-Agreeableness
MS <sub>4<sub>PG</sub></sub>	BFI-Openness
MS <sub>5<sub>PG</sub></sub>	BFI-Extroversion
MS <sub>6<sub>PG</sub></sub>	BFI-Neuroticism
MS <sub>7<sub>PG</sub></sub>	BFI-Conscientiousness

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

Table 11: Measures used for Pareto weight

Abbreviation	Activity
MS <sub>1<sub>BARG</sub></sub>	A woman who is in charge of most part of tasks of the household has no time to work*
MS <sub>2<sub>BARG</sub></sub>	Both spouses should contribute to household income*
MS <sub>3<sub>BARG</sub></sub>	It is better for everyone if the man goes to work and the woman takes care of the household and the family*
MS <sub>4<sub>BARG</sub></sub>	Men should assume a more active role in the household chores and childcare than what they actually do*
MS <sub>5<sub>BARG</sub></sub>	If my spouse earned enough there is no reason for me to work*
MS <sub>6<sub>BARG</sub></sub>	After having children, the best for a woman is to develop her career*
MS <sub>7<sub>BARG</sub></sub>	Taking into account the pros and cons, it is very important for me to have a paying job*
MS <sub>8<sub>BARG</sub></sub>	Having a payed job is the best way for a woman to become independent*
MS <sub>9<sub>BARG</sub></sub>	Father's and mother's time is equally important for the children*
MS <sub>10<sub>BARG</sub></sub>	It is better to have a bad marriage than to remain single*
MS <sub>11<sub>BARG</sub></sub>	Woman participates in the process of administering income (yes-no)
MS <sub>12<sub>BARG</sub></sub>	Man participates in the process of administering income (yes-no)
MS <sub>13<sub>BARG</sub></sub>	Both, father and mother participate in the process of administering income (yes-no)
MS <sub>14<sub>BARG</sub></sub>	(Mother) Who should take care of children (Father-Mother-Both-Other)
MS <sub>15<sub>BARG</sub></sub>	(Man) Women should only be in charge of taking care of children (yes-no)
MS <sub>16<sub>BARG</sub></sub>	(Man) Women should take care of children and work part time (yes-no)
MS <sub>17<sub>BARG</sub></sub>	(Man) Women should work full-time and delegate childcare to someone else (yes-no)
MS <sub>18<sub>BARG</sub></sub>	(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 12: Measures used for Skills at birth

Abbreviation	Activity
MS <sub>1</sub> <sub>BIRTH</sub>	Mother diagnosed with Preeclampsia during pregnancy
MS <sub>2</sub> <sub>BIRTH</sub>	Mother diagnosed with Cholestasis during pregnancy
MS <sub>3</sub> <sub>BIRTH</sub>	Mother diagnosed with Urinary infections during pregnancy
MS <sub>4</sub> <sub>BIRTH</sub>	Mother diagnosed with Hemorrhages during pregnancy
MS <sub>5</sub> <sub>BIRTH</sub>	Mother diagnosed with Hipertension during pregnancy
MS <sub>6</sub> <sub>BIRTH</sub>	Mother diagnosed with Placenta Previa during pregnancy
MS <sub>7</sub> <sub>BIRTH</sub>	Mother diagnosed with Diabetes G during pregnancy
MS <sub>8</sub> <sub>BIRTH</sub>	Mother diagnosed with Anemia during pregnancy
MS <sub>9</sub> <sub>BIRTH</sub>	Mother diagnosed with Toxoplasmosis during pregnancy
MS <sub>10</sub> <sub>BIRTH</sub>	Mother diagnosed with Depression during pregnancy
MS <sub>11</sub> <sub>BIRTH</sub>	Mother diagnosed with Bipolar D. during pregnancy
MS <sub>12</sub> <sub>BIRTH</sub>	Mother diagnosed with Anxiety D. during pregnancy
MS <sub>13</sub> <sub>BIRTH</sub>	Mother diagnosed with Obsesive compulsive D. during pregnancy
MS <sub>14</sub> <sub>BIRTH</sub>	Mother diagnosed with Fobia during pregnancy
MS <sub>15</sub> <sub>BIRTH</sub>	Mother diagnosed with Panic D. during pregnancy
MS <sub>16</sub> <sub>BIRTH</sub>	Mother diagnosed with PTSD during pregnancy
MS <sub>17</sub> <sub>BIRTH</sub>	Cigarettes consumed during pregnancy
MS <sub>18</sub> <sub>BIRTH</sub>	Cigarettes consumed during the first six months of life of child
MS <sub>19</sub> <sub>BIRTH</sub>	Alcohol consumption during pregnancy*
MS <sub>20</sub> <sub>BIRTH</sub>	Substance abuse during pregnancy*
MS <sub>21</sub> <sub>BIRTH</sub>	Child was born pre-term
MS <sub>22</sub> <sub>BIRTH</sub>	Weight at birth (grams)
MS <sub>23</sub> <sub>BIRTH</sub>	Height at birth (cm)

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

Table 13: Measures used for Investment in 2012

Abbreviation	Activity
MS <sub>1INV,12</sub>	Consumption of hamburger-pizza-fries*
MS <sub>2INV,12</sub>	Consumption of Fish-Beef-Chicken*
MS <sub>3INV,12</sub>	Consumption of bread-rice-pasta
MS <sub>4INV,12</sub>	Consumption of legumes*
MS <sub>5INV,12</sub>	Consumption of Chocolate-Candy*
MS <sub>6INV,12</sub>	Consumption of juice*
MS <sub>7INV,12</sub>	Consumption of snacks in bags*
MS <sub>8INV,12</sub>	Consumption of milk*
MS <sub>9INV,12</sub>	Consumption of water*
MS <sub>10INV,12</sub>	Consumption of cookies*
MS <sub>11INV,12</sub>	Consumption of fruits and vegetables*
MS <sub>12INV,12</sub>	There are two or more toys in the household where child can learn colors, sizes and shapes
MS <sub>13INV,12</sub>	Child has three or more puzzles
MS <sub>14INV,12</sub>	There is a music device where child can listen children's music
MS <sub>15INV,12</sub>	There are two or more toys for free expression or impersonations such as tools and customs
MS <sub>16INV,12</sub>	There are two or more toys in the household that can help with learning numbers
MS <sub>17INV,12</sub>	There are at least ten children's books available in the house
MS <sub>18INV,12</sub>	There are at least ten books for adults
MS <sub>19INV,12</sub>	At first sight, there is very little evidence that there is a child living in the household
MS <sub>20INV,12</sub>	Number of people with whom child shares bed
MS <sub>21INV,12</sub>	Number of people with whom child shares room

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

Table 14: Measures used for Investments in 2010

Abbreviation	Activity
$MS_{1_{INV},10}$	Child has a special place where to store toys and belongings
$MS_{2_{INV},10}$	Child has at least one toy that involves muscular activity
$MS_{3_{INV},10}$	Child has toys to pull and push
$MS_{4_{INV},10}$	Child has at least one toy with wheels
$MS_{5_{INV},10}$	Availability of plush toys-stuffed animals
$MS_{6_{INV},10}$	Availability of mobiles for child
$MS_{7_{INV},10}$	Availability of musical or literary toys
$MS_{8_{INV},10}$	Child has three or more books of his own

Table 15: **Father's opinion on gender roles**

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

Table 16: Summary statistics-Measures of bargaining power

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

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



Table 17: Time investments and labor supply (2010)

$$\text{Effort}_i = \beta_0 + \beta_1 \text{Mother works}_i + \beta_2 \text{Father works}_i + \beta_3 X_i + \varepsilon_i$$

VARIABLES	(1) Mother's effort (2010)	(2) Mother's effort (2010)	(3) Father's effort (2010)	(4) Father's effort (2010)
Mother works	-0.46 (0.29)	-0.71** (0.33)	0.52 (0.33)	0.31 (0.37)
Father works	1.50*** (0.46)	1.44*** (0.49)	-0.26 (0.49)	-0.06 (0.54)
Total household income (\$1,000 CLP)	0.00 (0.03)	0.01 (0.03)	0.09*** (0.03)	0.10*** (0.03)
Age of child (months)	0.04** (0.02)	0.03 (0.02)	-0.01 (0.02)	-0.02 (0.02)
BFI-Kindness	0.04 (0.15)	0.08 (0.17)	0.01 (0.17)	0.01 (0.19)
BFI-Openness	0.25* (0.14)	0.15 (0.16)	-0.03 (0.15)	-0.23 (0.17)
BFI-Extraversion	0.36** (0.15)	0.39** (0.17)	0.34** (0.16)	0.48*** (0.18)
BFI-Neuroticism	-0.45*** (0.15)	-0.31* (0.18)	-0.23 (0.16)	-0.22 (0.18)
BFI-Responsibility	-0.03 (0.15)	0.08 (0.16)	0.20 (0.16)	0.27 (0.19)
Wais-digits	0.18 (0.14)	0.23 (0.15)	0.24 (0.17)	0.10 (0.19)
Wais-Vocabulary	-0.12 (0.16)	-0.13 (0.17)	-0.34* (0.18)	-0.30 (0.20)
Number of siblings	-0.72*** (0.16)	-0.88*** (0.19)	-0.32* (0.19)	-0.54*** (0.20)
PSI-P Total		-0.12 (0.16)		-0.22 (0.17)
Observations	950	759	950	759
Adjusted R-squared	0.07	0.07	0.03	0.04

Robust standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

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

Table 18: Time investments and labor supply (2012)

$$\text{Effort}_i = \beta_0 + \beta_1 \text{Mother works}_i + \beta_2 \text{Father works}_i + \beta_3 X_i + \varepsilon_i$$

VARIABLES	(1) Mother's effort (2012)	(2) Mother's effort (2012)	(3) Father's effort (2012)	(4) Father's effort (2012)
Mother works	-0.11 (0.13)	-0.12 (0.15)	0.27*** (0.11)	0.26** (0.12)
Father works	0.12 (0.21)	0.09 (0.24)	-0.07 (0.17)	-0.27 (0.21)
Total household income (\$1,000 CLP)	-0.02 (0.02)	-0.03 (0.02)	0.01 (0.02)	-0.00 (0.02)
Age of child (months)	-0.02*** (0.01)	-0.02** (0.01)	-0.01** (0.01)	-0.01** (0.01)
BFI-Kindness	0.04 (0.07)	0.05 (0.08)	-0.00 (0.05)	-0.01 (0.05)
BFI-Openness	0.16** (0.07)	0.19*** (0.07)	0.02 (0.05)	0.06 (0.05)
BFI-Extraversion	-0.02 (0.07)	-0.07 (0.09)	-0.04 (0.06)	-0.09 (0.07)
BFI-Neuroticism	-0.09 (0.07)	-0.05 (0.08)	-0.07 (0.05)	-0.05 (0.06)
BFI-Responsibility	0.06 (0.07)	0.08 (0.08)	0.11** (0.05)	0.10* (0.06)
Wais-digits	0.16** (0.07)	0.17** (0.08)	0.07 (0.05)	0.06 (0.05)
Wais-Vocabulary	0.11 (0.07)	0.11 (0.08)	0.08 (0.07)	0.10 (0.07)
Number of siblings	-0.08 (0.08)	-0.12 (0.09)	-0.12** (0.06)	-0.16** (0.06)
PSI-P Total		-0.17** (0.08)		-0.11* (0.06)
Observations	950	759	950	759
Adjusted R-squared	0.04	0.05	0.04	0.04

Robust standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

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

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

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

Robust standard errors in parentheses

\*\*\* p&lt;0.01, \*\* p&lt;0.05, \* p&lt;0.1

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

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

Robust standard errors in parentheses

\*\*\* p&lt;0.01, \*\* p&lt;0.05, \* p&lt;0.1

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

Table 21: Female empowerment and Child outcomes

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

Robust standard errors in parentheses

\*\*\* p&lt;0.01, \*\* p&lt;0.05, \* p&lt;0.1

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

Table 22: Summary statistics-Variables determining Pareto weight

Variable	Mean	(Std. Dev.)
Father's non-labor income share	0.28	(0.35)
Age difference (Father-Mother)	2.89	(5.19)
Difference in grades attained (Father-Mother)	-0.55	(2.84)
Sex ratio in region (Women/Men)	1	(0.07)
Unemployment ratio in region (Men/Women)	0.67	(0.11)
Wage ratio in region (Men/Women)	1.21	(0.07)
Distance to women protection center (km)	18.93	(31.68)
N	950	

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

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

Parameter	Estimate	Standard Error
$\alpha_{1,12}^m$	0.6345	0.0734
$\alpha_{2,12}^m$	0.0520	0.0264
$\alpha_{3,12}^m$	0.2997	0.0449
$\alpha_{4,0,12}^m$	0.0137	0.0386
$\alpha_{4,1,12}^m$	0.0032	0.0151
$\alpha_{1,10}^m$	0.4311	0.0386
$\alpha_{2,10}^m$	0.0219	0.0631
$\alpha_{3,10}^m$	0.2178	0.0514
$\alpha_{4,0,10}^m$	0.0042	0.0513
$\alpha_{4,1,10}^m$	0.0040	0.0035
$\alpha_{5,10}^m$	0.3249	0.0586

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

Parameter	Estimate	Standard Error
$\alpha_{1,12}^f$	0.1651	0.0808
$\alpha_{2,12}^f$	0.0119	0.0754
$\alpha_{3,12}^f$	0.8197	0.1274
$\alpha_{4,0,12}^f$	0.0034	0.0089
$\alpha_{4,1,12}^f$	0.0018	0.0782
$\alpha_{1,10}^f$	0.1788	0.0444
$\alpha_{2,10}^f$	0.3020	0.1153
$\alpha_{3,10}^f$	0.8197	0.0889
$\alpha_{4,0,10}^f$	0.0243	0.0114
$\alpha_{4,1,10}^f$	0.0000	0.0337
$\alpha_{5,10}^f$	0.0089	0.0352

Table 25: Estimates: Preference shock

Parameter	Estimate	Standard Error
$\sigma_{W,A}^m$	3.663	0.392
$\sigma_{NW,A}^m$	1.000	0.034
$\sigma_{W,NA}^m$	1.159	0.182
$\sigma_{NW,NA}^m$	1.518	0.118
$\sigma_{W,A}^f$	0.502	0.005
$\sigma_{NW,A}^f$	1.000	0.124
$\sigma_{W,NA}^f$	1.915	0.150
$\sigma_{NW,NA}^f$	0.997	0.125

Preference shocks for childcare-no work-are standardized to one.

Table 26: Estimates: Mothers wages

Parameter	Estimate	Standard Error
$\beta_0^m$	5.787	0.592
$\beta_1^m$	0.276	0.099
$\beta_2^m$	0.072	0.008
$\beta_3^m$	-0.001	0.012
$\sigma_{w_m}$	0.828	0.096

Table 27: Estimates: Fathers wages

Parameter	Estimate	Standard Error
$\beta_0^f$	5.810	0.702
$\beta_1^f$	0.126	0.002
$\beta_2^f$	0.187	0.087
$\beta_3^f$	-0.002	0.059
$\sigma_{w_f}$	0.690	0.053

Table 28: Estimates: Production of Skills

Parameter	Estimate	Standard Error
$\theta_0$	0.213	0.068
$\theta_1$	0.267	0.051
$\theta_2$	0.520	0.101
$\phi$	0.469	0.012
$\gamma_f$	0.498	0.057
$\gamma_m$	0.502	0.126
$\delta_0$	-0.800	0.075
$\delta_1$	-0.000	0.043
$\delta_2$	0.001	0.057
$\delta_{3,10}$	3.504	0.299
$\delta_{3,12}$	5.300	0.652
$\delta_4$	0.013	0.020
$\sigma_s$	1.575	0.165

Table 29: Estimates: Pareto weight

Parameter	Estimate	Standard Error	Description
$\lambda_0$	-1.477	0.191	Intercept
$\lambda_1$	0.001	0.018	Wage ratio
$\lambda_2$	0.017	0.039	Non-labor income ratio
$\lambda_3$	-0.060	0.045	Age difference
$\lambda_4$	0.002	0.008	Educational difference
$\lambda_5$	-2.532	0.352	Gender ratio
$\lambda_6$	-0.001	0.025	Unemployment ratio
$\lambda_7$	-0.528	0.058	Wage ratio (province)
$\lambda_8$	0.004	0.001	Distance to center
$\sigma_\mu$	0.560	0.013	Standard deviation



Table 30: Estimates: Prices

Parameter	Estimate	Standard Error
$\text{Price}_{I_0}$	966.238	113.702
$\text{Price}_{I_1}$	0.638	0.056
$\text{Pchildcare}_0$	2440.602	287.139
$\text{Pchildcare}_1$	622.610	73.268

Table 31: Estimates: Distribution of latent factors

Parameter	Estimate	Standard Error
$\sigma_{ef}^m$	2.513	0.316
$\sigma_{ef}^f$	3.375	0.424
$\sigma_{inv}$	2.190	0.242

Table 32: Model Fit - I

Female Labor Force Participation	Predicted	Data
2010	63.38%	60.28%
2012	63.7%	61.6%

Table 33: Model Fit - II

Male Labor Force Participation	Predicted	Data
2010	91.8%	91.6%
2012	93.1%	91.0%

Table 34: Model Fit - III

Childcare Attendance	Predicted	Data
Working Mothers	78.3%	74.04%
Not-working Mothers	53.7%	52.1%
Total	68.5%	65.34%

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

Counterfactual	Effect on Female employment
1	-0.32
2	-0.32
3	0.74
4	0.00

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

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

Table 37: Effects of Policy counterfactuals. Change in Mother's effort (standard deviations)

Counterfactual	Change in Mother's Effort (Standard Deviations)
1	0.03
2	0.03
3	-0.37
4	0.00

Table 38: Effects of Policy counterfactuals. Change in Father's effort (standard deviations)

Counterfactual	Change in Father's Effort (Standard Deviations)
1	0.04
2	0.04
3	-0.33
4	0.00

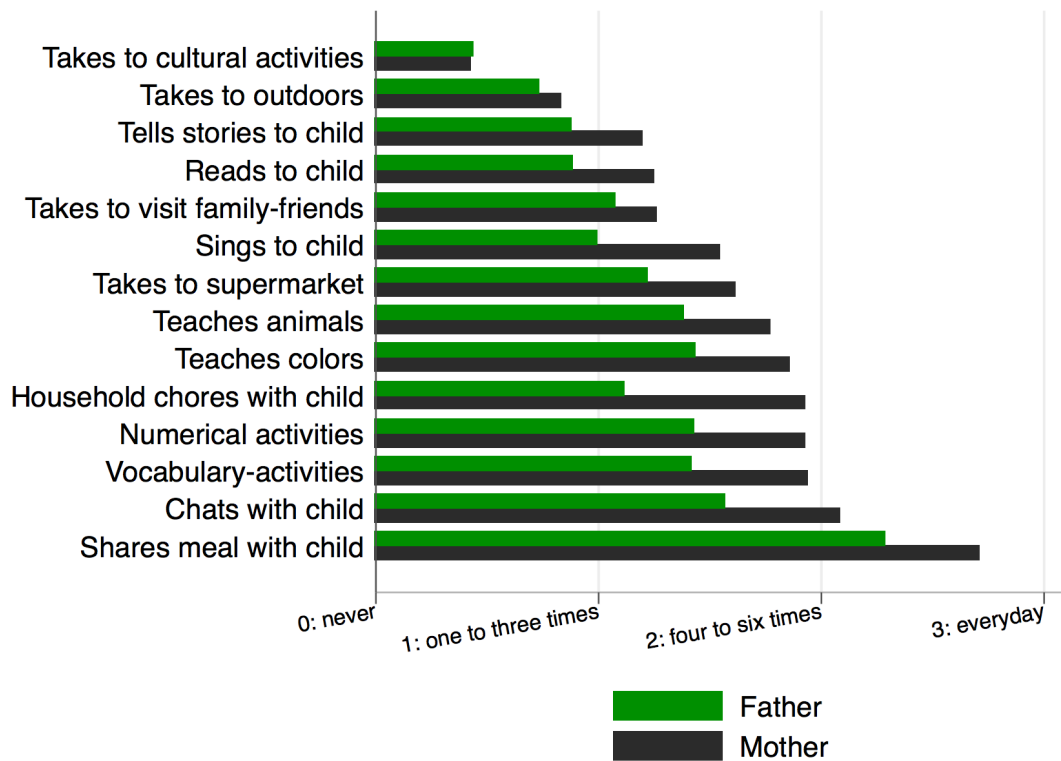
Table 39: Effects of Policy counterfactuals. Change in Money invested

Counterfactual	Change in Money Invested
1	10.79
2	10.79
3	7.09
4	311.96

Table 40: Effects of Policy counterfactuals. Gaps in skills between the lowest and the richest income quintiles. Measured in Standard Deviations.

Counterfactual	20-20 gap in Skills
Initial situation	-1.02495
1	-1.00323
2	-1.00323
3	-1.00680
4	-0.78363

Figure 1: Weekly frequency of activities between parents and children



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

Figure 2: Gaps in health at birth (%)

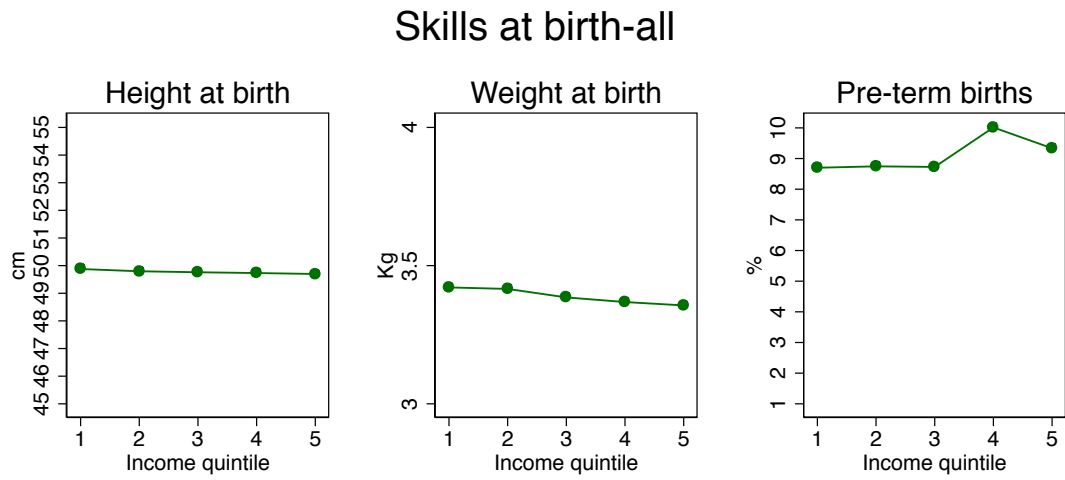


Figure 3: Gaps in skills at age 5

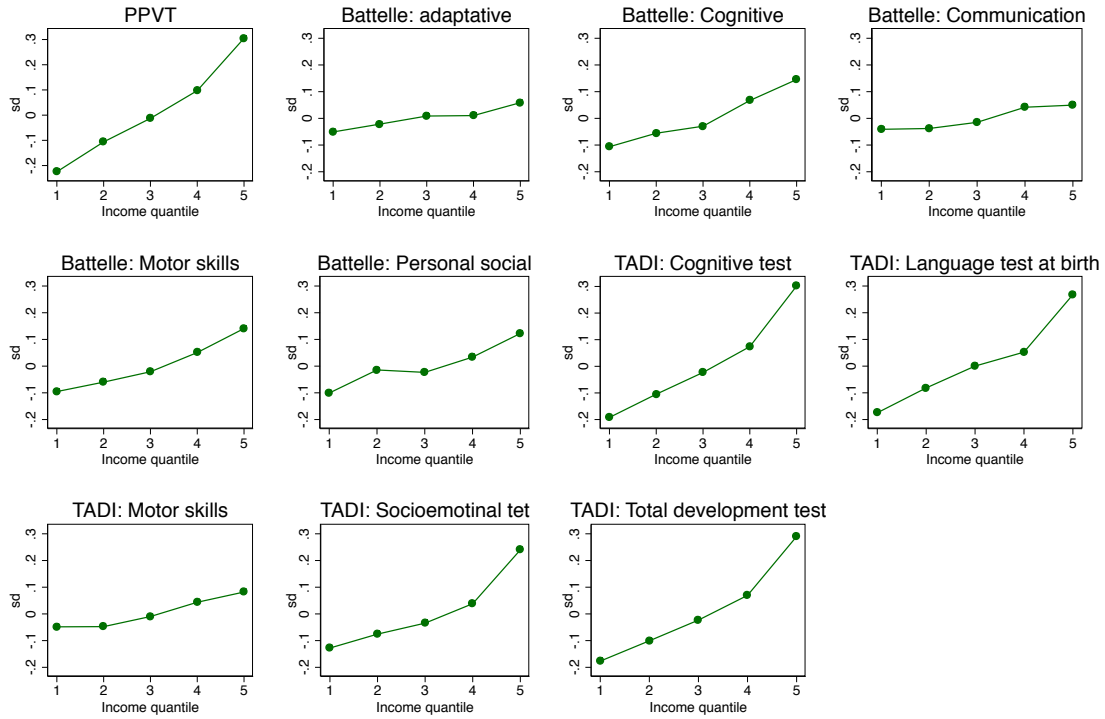


Figure 4: Mother's labor force participation (%)

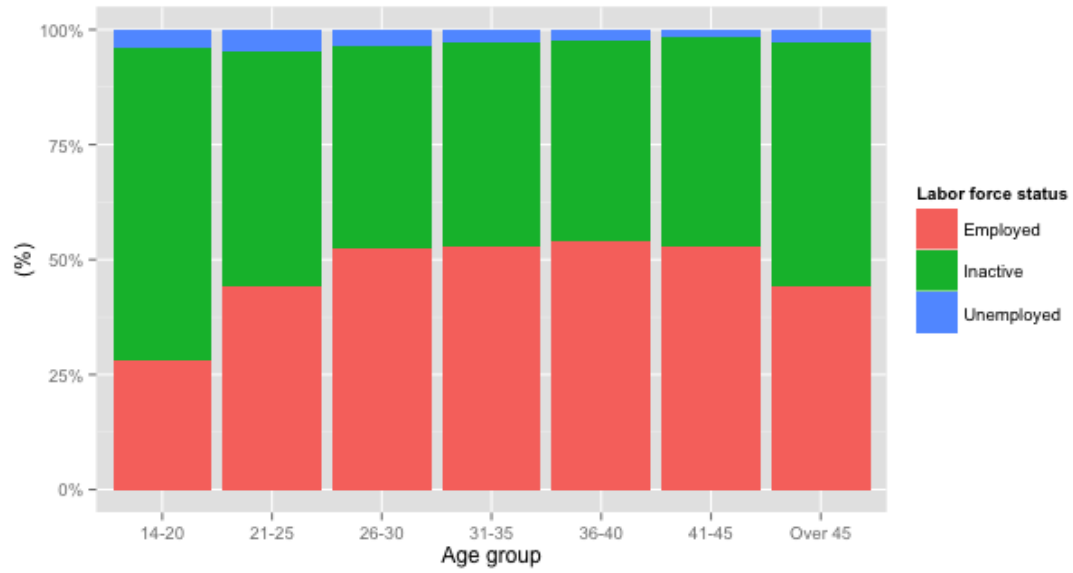


Figure 5: Instruments for supply of goods for children

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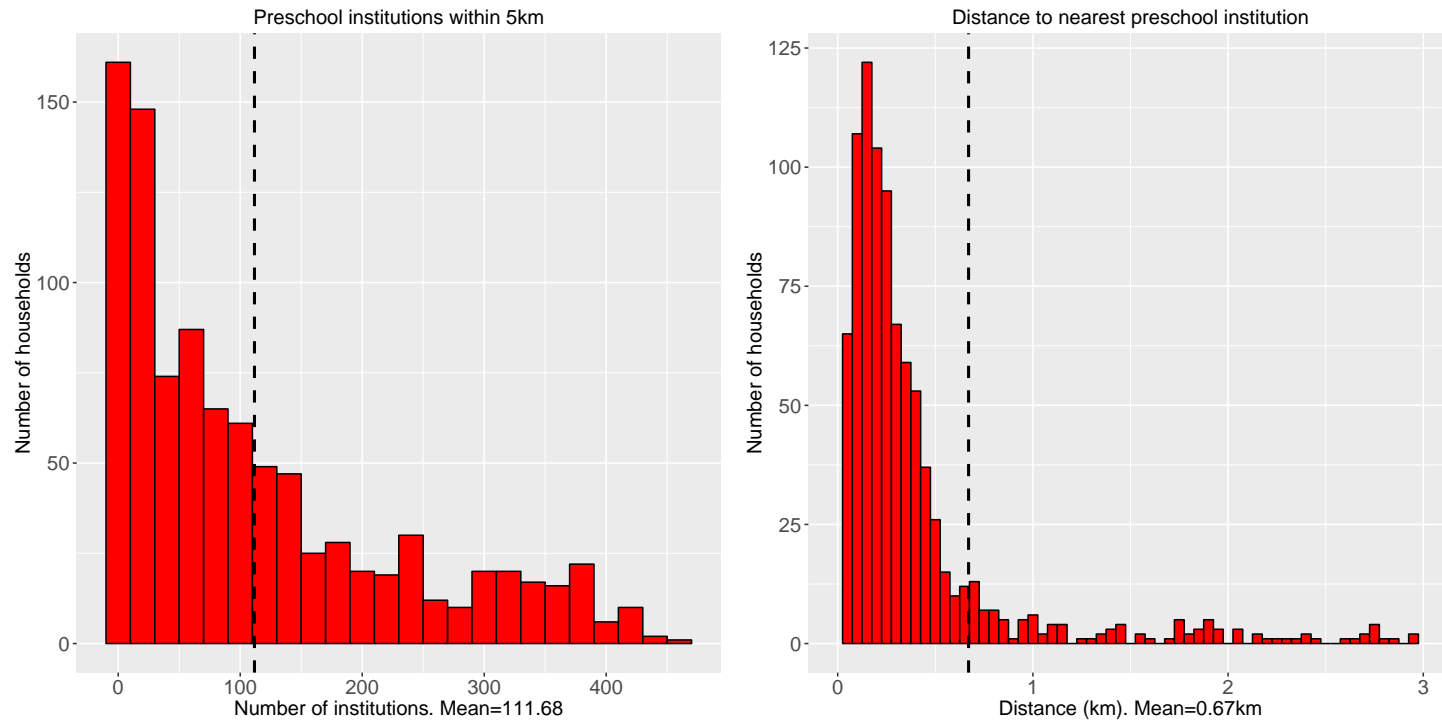


Figure 6: Model fit: Female labor force participation

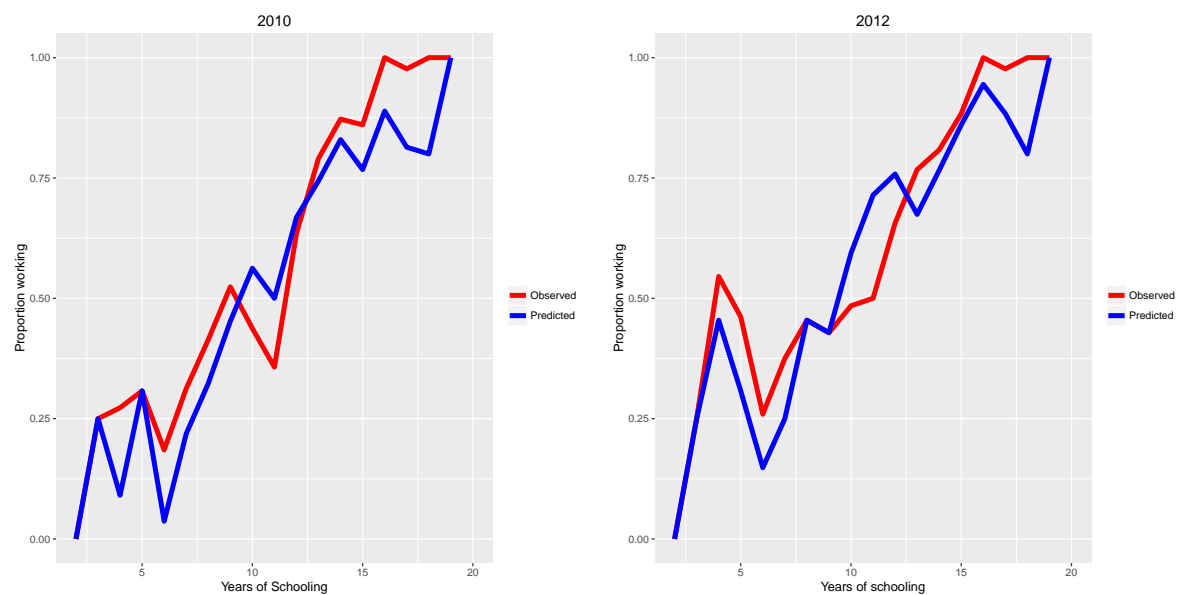




Figure 7: Model fit: Female labor force participation

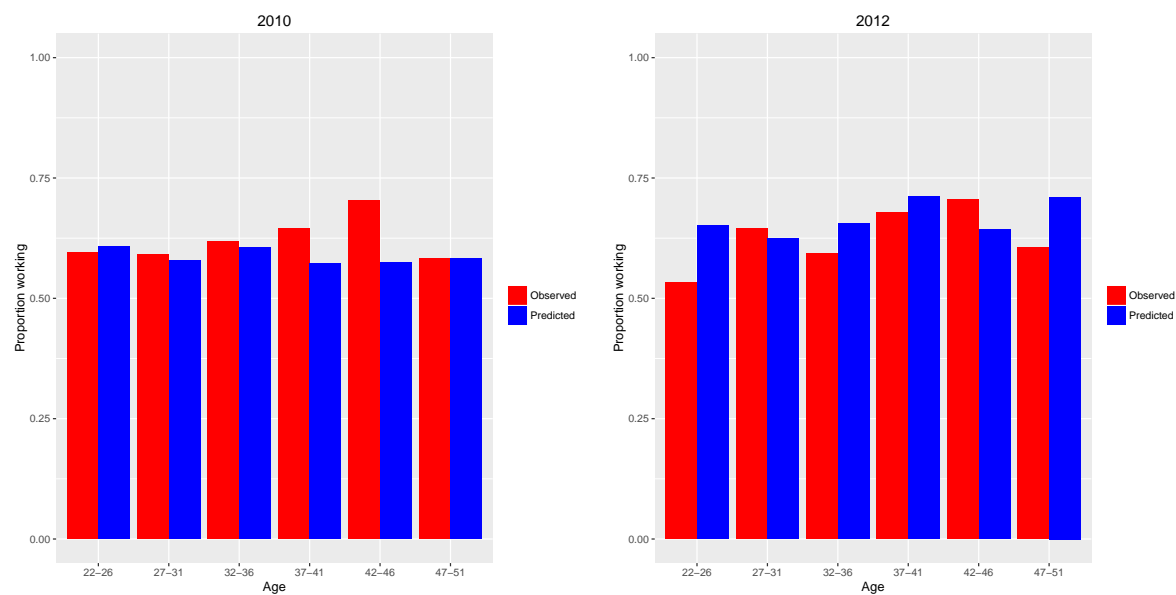


Figure 8: Model fit: Male labor force participation

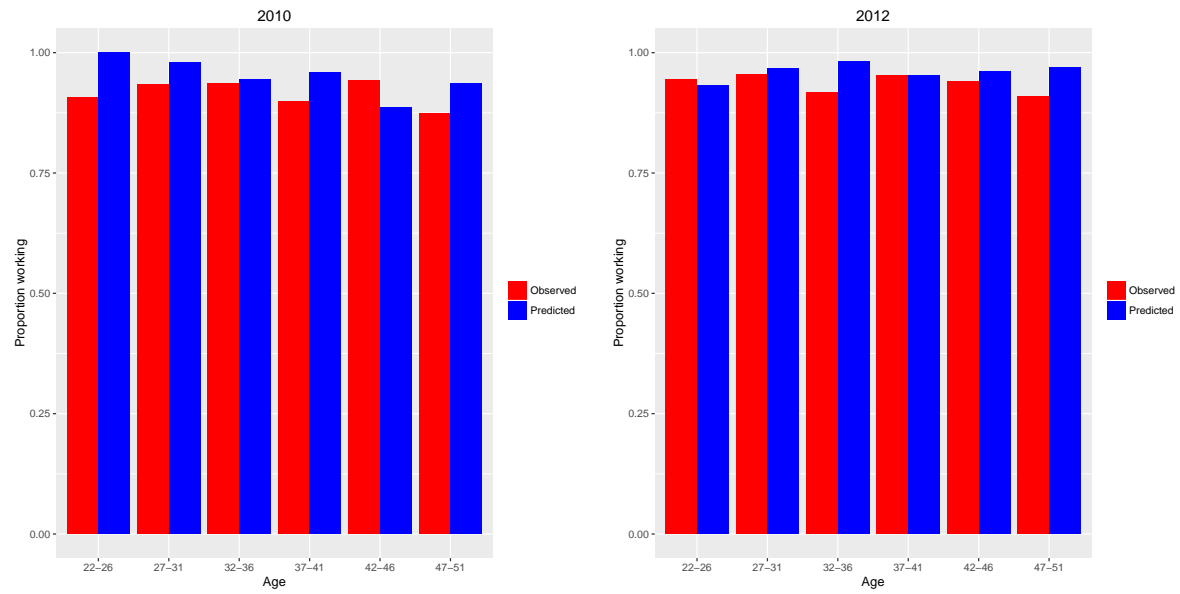


Figure 9: Model fit: Childcare attendance

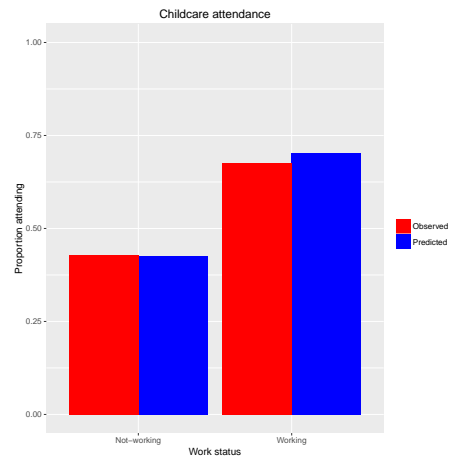
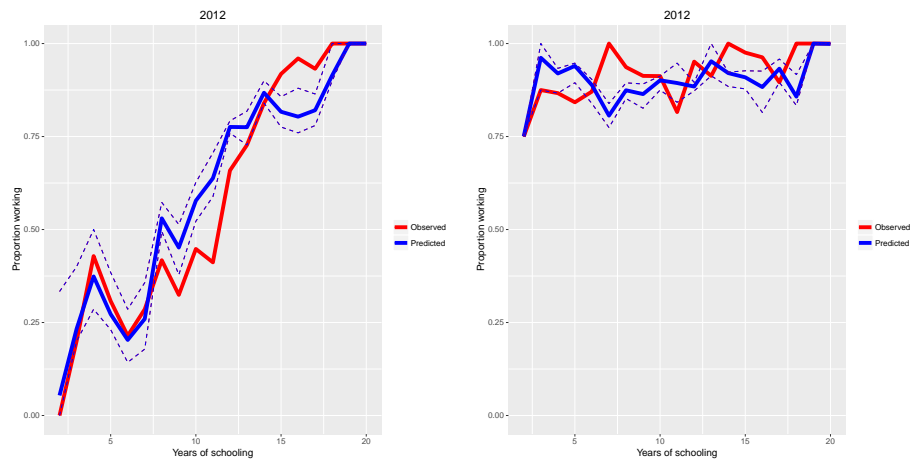
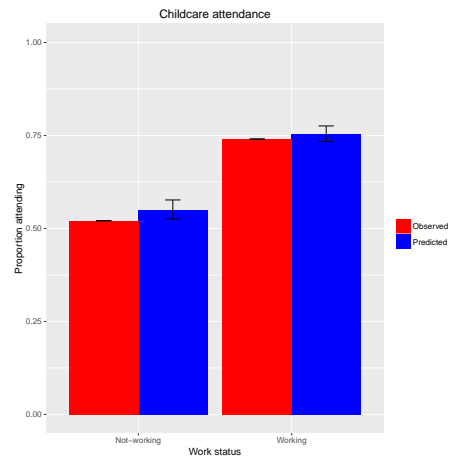


Figure 10: Bootstrap fit: Parents' Labor Force Participation in 2012



Dashed lines represent the 95% confidence interval

Figure 11: Bootstrap fit: Childcare decisions (%)



Brackets include the 95% confidence interval

Figure 12: Distribution of skills. Smoothing distribution

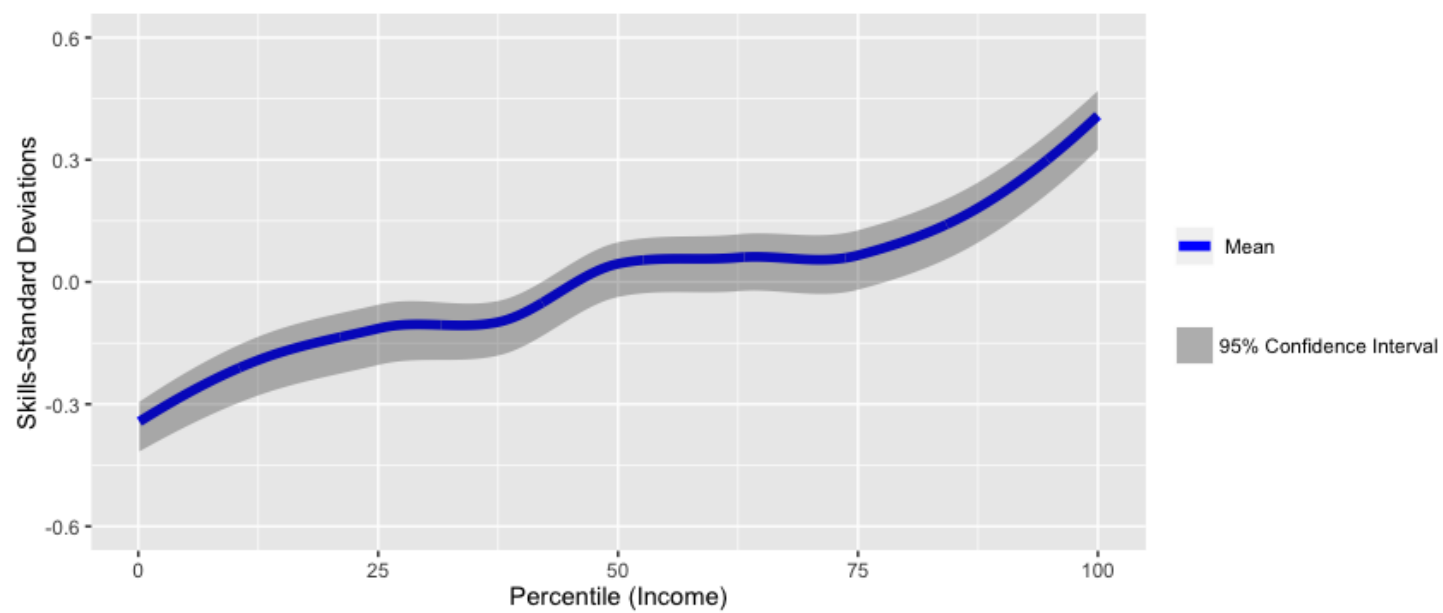
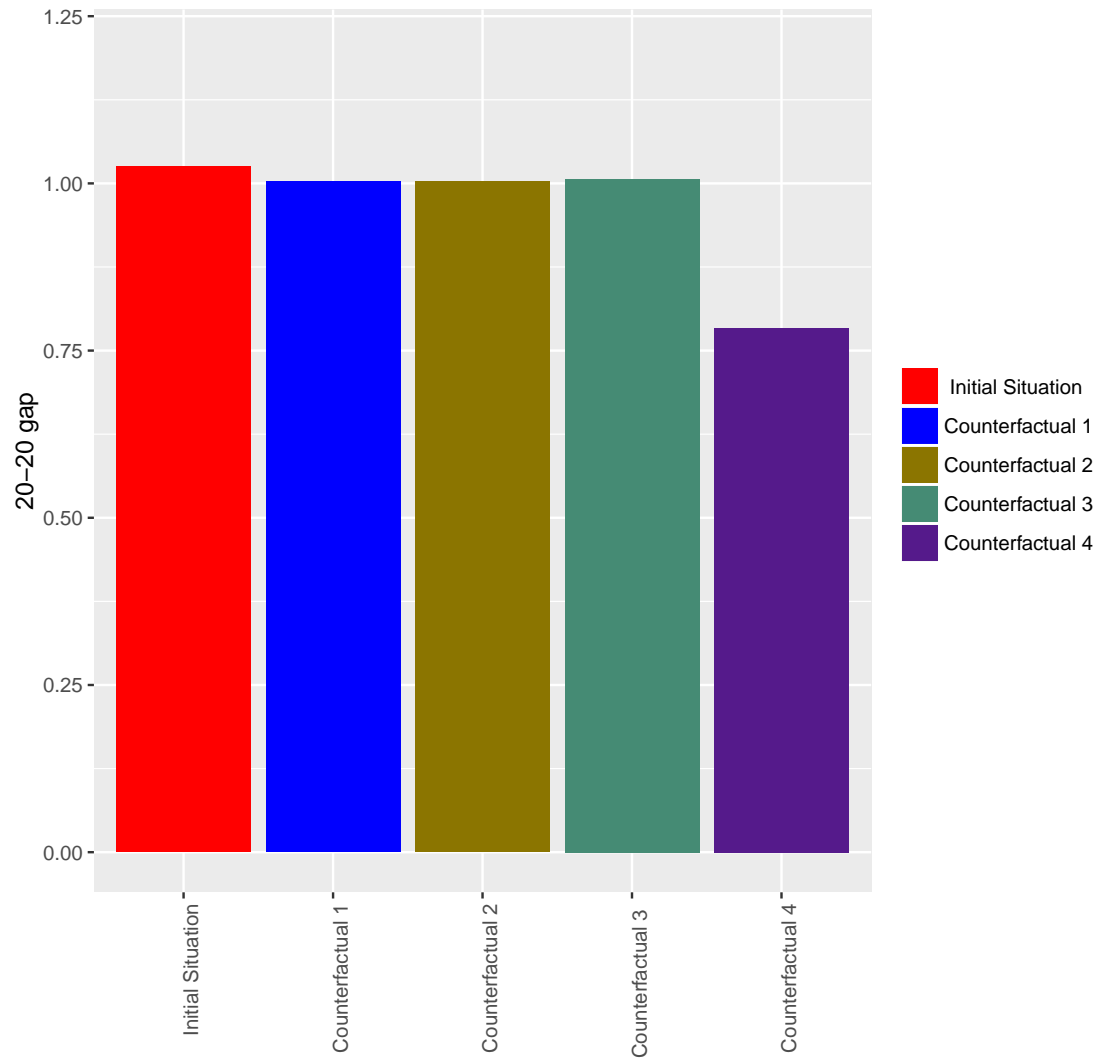


Figure 13: Effects of Policy Experiments

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



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## 11 Appendix

### 11.1 Identification of Measurement System

The measurement system is described by:

$$Z = \iota_0 + \iota_1 K + \varepsilon \quad (54)$$

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

$$\Sigma_Z = \iota_1 \Sigma_K \iota_1' + \Sigma_\varepsilon \quad (55)$$

The matrix of moments  $\Sigma_Z$  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:

$$M = \sum_{k \in K} N_k = 151 \quad (56)$$

as we have

$$N_{ln(S_0)} = 23$$

$$N_{ln(S_1)} = 11$$

$$N_{ln(S_2)} = 13$$

$$N_{ln(PG)} = 8$$

$$N_\mu = 19$$

$$N_{ln(I_1)} = 8$$

$$N_{ln(I_2)} = 21$$

$$N_{ln(\hat{e}_1^f)} = 10$$

$$N_{ln(\hat{e}_2^f)} = 14$$

$$N_{ln(\hat{e}_1^m)} = 10$$

$$N_{ln(\hat{e}_2^m)} = 14$$

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  $\iota_1$  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  $\Sigma_K$  contains  $(11 \times (11 + 1)/2)$  covariances to be estimated and  $\Sigma_\varepsilon$  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  $\varepsilon_m^{\ln(s_0)} \perp \varepsilon_m^k$  for  $m = 1 \dots N_{\ln(s_0)}$ ,  $k \in K, k \neq \ln(s_0)$ ,  $m' = 1 \dots N_k$  we have enough moments to identify the system. By doing this assumption, we are assuming that the elements in  $\Sigma_\varepsilon$  that correspond corresponding to  $\ln(s_0)$  and other factors are zero. With this, we have enough moments to identify the system.

## 11.2 Estimation

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

### 11.2.1 Likelihood function

The likelihood of the model is:

$$\begin{aligned}\mathcal{L}(\Theta|O; X) &= P(O|X; \Theta) = P(O_1, O_2, O_3|X; \Theta) \\ p_0(O_0|\Theta, X) p_1(O_1|O_0, \Theta, X) p_2(O_2|O_1, \Theta, X)\end{aligned}\tag{57}$$

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.

$$\begin{aligned}p_0(O_0|\Theta, X) &= \int p_0(O_0, K_0|\Theta, X) dK_0 = \\ &\int p_0(O_0|K_0, \Theta, X) p(K_0|\Theta, X) dK_0 = \\ &E_{p(K_0|\Theta, X)} [P_0(O_0|K_0, \Theta, X)] \approx \\ &\sum_{rr=1}^{RR} P_0(O_0|K_0^{\{rr\}}, \Theta, X)\end{aligned}\tag{58}$$

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

$$K_0 = \{\ln(s_0), \ln(PG)\}\tag{59}$$

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

measurement system of the unobserved latent factors and averaging such likelihoods over the  $RR$  shocks.

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

$$K_1 = \{\ln(s_1), \ln(\hat{e}_1^f), \ln(\hat{e}_1^m), \ln(\hat{I}_1)\} \quad (60)$$

and the likelihood can be expressed as:

$$\begin{aligned} p_1(O_1|O_0, \Theta, X) &= \int p_1(O_1, K_1|O_0, \Theta, X) dK_1 = \\ &\int \int p_1(O_1, K_1, K_0|O_0, \Theta, X) dK_1 dK_0 = \\ &\int \int p_1(O_1|K_1, K_0, O_0, \Theta, X) p(K_1|O_0, K_0, \Theta, X) p(K_0|O_0, \Theta, X) dK_1 dK_0 \end{aligned} \quad (61)$$

Note that

$$p(K_1|O_0, K_0, \Theta, X) = p(K_1|K_0, \theta, X) \quad (62)$$

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

$$p_1(O_1|K_1, K_0, O_0, \Theta, X) = p_1(O_1|K_1, \Theta, X) \quad (63)$$

Taking into account the facts presented in Equations 62 and 63 we can express 61 as:

$$\begin{aligned} &\int \int p_1(O_1|K_1, \Theta, X) p(K_1|K_0, \Theta, X) p(K_0|O_0, \Theta, X) dK_1 dK_0 = \\ &\int p(K_0|O_0, \Theta, X) \left[ \int p(O_1|K_1, \Theta, X) p(K_1|K_0, \Theta, X) dK_1 \right] dK_0 = \\ &E_{p(K_0|O_0, \Theta, X)} \left[ \int p(O_1|K_1, \Theta, X) p(K_1|K_0, \Theta, X) dK_1 \right] = \end{aligned} \quad (64)$$

in Equation 64  $p(O_1|K_1, \Theta, X)$  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:

$$\begin{aligned} p(O_1|K_1, \Theta, X) = \\ p(Z_1|K_1, \Theta, X) \times p(w^f|K_1, \Theta, X)^{(1-h^{f,*})} \times p(w^m|K_1, \Theta, X)^{1-h^{m,*}} \\ \times p(h^{f,*}, h^{m,*}, a|w^f, w^m, K_1, \Theta, X) \end{aligned} \quad (65)$$

As specified previously,  $p(Z_1|K_1, \Theta, X)$  is given by the measurement system.  $p(w^f|K_1, \Theta, X)$  is given by the measurement error associated to the observed wages:

$$w^j = \beta_0^j + \beta_1^j yr school^j + \beta_2 Age^j + \beta + 3(Age^j)^2 + \varepsilon_{wj} \quad (66)$$

where  $\varepsilon_{wj}$  is measurement error following a distribution  $\varepsilon_{wj} \sim N(0, \sigma_{\varepsilon^j})$ .

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:

$$\begin{aligned} p(h_f^*, h_m^*, a^*|w^f, w^m, K_1, \Theta, X) = \\ p_{(\varepsilon_d^f, \varepsilon_d^m)} \left( W(u^f(h^{f,*}, h^{m,*}, a^*), u^m(h^{f,*}, h^{m,*}, a^*)) \in \arg \max_{\{h^f, h^m, a\}} W(u^f(h^f, h^m, a), u^m(h^f, h^m, a)) | K_1, \Theta, X \right) \end{aligned} \quad (67)$$

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

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

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

$$\int p(\ln(s_1), \ln(\hat{e}_1^f), \ln(\hat{e}_1^m), \ln(\hat{I}_1), \mu_1 | \ln(PG), \ln(s_0), \Theta, X) d\mu =$$

$$\int p(\ln(s_1) | \ln(\hat{e}_1^f), \ln(\hat{e}_1^m), \ln(\hat{I}_1), \mu_1, \ln(PG), \ln(s_0), \Theta, X) d\mu \quad (68)$$

$$\times \int p(\ln(\hat{e}_1^f) | \mu_1, \Theta, X) d\mu \quad (69)$$

$$\times \int p(\ln(\hat{e}_1^m) | \mu_1, \Theta, X) d\mu \quad (70)$$

$$\times \int p(\ln(\hat{I}_1) | \mu_1, \Theta, X) d\mu \quad (71)$$

We integrate over the factor  $\mu$  given that we have no measures for it during the first period. The term 68 is given by the production of skills and the remaining 69-71 are given by the distribution of heterogeneity in each factor:  $\eta_{ef}$ ,  $\eta_{em}$  and  $\eta_I$ . Note that we can also use Monte-Carlo techniques to approximate the expression in 64 by:

$$\sum_{rr=1}^{RR} \hat{w}_0^{\{rr\}} \left[ \int p(O_1|K_1, \Theta, X) p(K_1|K_0^{\{rr\}}, \Theta, X) dK_1 \right] \quad (72)$$

where  $\{K_0^{\{rr\}}\}_{rr=1}^{RR}$  are drawn from an importance distribution  $g_0(K_0|Z_0, \Theta, X)$  and the weights are given by:

$$\hat{w}_0^{rr} = \frac{w_0^{rr}}{\sum_{rr=1}^{RR} w_0^{rr}} \quad (73)$$

and the individual weights are defined:

$$w_0^{rr} \propto \frac{p(K_0|O_0, \Theta, X)}{g_0(K_0|Z_0, \theta_0, \Theta, X)} \quad (74)$$

Note that after some algebra, we can define:

$$\tilde{w}_1 = \frac{p(O_1|K_1, \Theta, X)p(K_1|K_0, \Theta, X)}{g_t(K_0|O_0, O_1, \Theta, X)} \quad (75)$$

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 75 into 64 we obtain:

$$\begin{aligned} \sum_{rr=1}^{RR} \hat{w}_0^{\{rr\}} \left[ \int p(O_1|K_1, \Theta, X)p(K_1|K_0^{\{rr\}}, \Theta, X) dK_1 \right] = \\ \sum_{rr=1}^{RR} \hat{w}_0^{\{rr\}} \left[ \sum_{rr'=1}^{RR} \tilde{w}_1^{rr'}(rr) \right] \end{aligned} \quad (76)$$

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:

$$p_1(O_1|K_1, K_0, O_0, \Theta, X) = \sum_{rr=1}^{RR} \hat{w}_0^{rr} \tilde{w}_1^{rr} \quad (77)$$

The computation of the likelihood for the second period is identical to that of the first period with the exception that we do not need to integrate over the factor  $\mu$  given that we have a set of



measures for it. In particular:

$$p(K_2|K_1, \Theta, X) = p(\ln(s_2), \ln(\hat{e}_2^f), \ln(\hat{e}_2^m), \ln(\hat{I}_2), \mu_2 | \ln(PG), \ln(s_1), \Theta, X) =$$

$$p(\ln(s_2) | \ln(\hat{e}_2^f), \ln(\hat{e}_2^m), \ln(\hat{I}_2), \mu_2, \ln(PG), \ln(s_1), \Theta, X) = \quad (78)$$

$$\times p(\ln(\hat{e}_2^f) | \mu_2 \Theta, X) = \quad (79)$$

$$\times p(\ln(\hat{e}_2^m) | \mu_2, \Theta, X) = \quad (80)$$

$$\times p(\ln(\hat{I}_2) | \mu_2 \Theta, X) = \quad (81)$$

$$\times p(\mu_2 | \Theta, X) \quad (82)$$

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 \(2012\)](#). The distribution  $p(\mu_2 | \Theta, X)$  is given by the corresponding transformation from from Equation [12](#)

### 11.3 Estimates of Measurement System

Table 41: Estimates: Measurement system -Skills in 2010

Parameter	Estimate	Standard Error
MS <sub>1,10</sub>	0.168	0.059
SDS <sub>1,10</sub>	2.506	0.079
MS <sub>2,10</sub>	0.119	0.051
SDS <sub>2,10</sub>	2.559	0.165
MS <sub>3,10</sub>	0.110	0.040
SDS <sub>3,10</sub>	2.364	0.166
MS <sub>4,10</sub>	-0.610	0.033
SDS <sub>4,10</sub>	2.046	0.072
MS <sub>5,10</sub>	-0.508	0.069
SDS <sub>5,10</sub>	2.286	0.104
MS <sub>6,10</sub>	-0.324	0.029
SDS <sub>6,10</sub>	2.645	0.076
MS <sub>7,10</sub>	-0.403	0.008
SDS <sub>7,10</sub>	2.408	0.088
MS <sub>8,10</sub>	-0.332	0.032
SDS <sub>8,10</sub>	2.265	0.129
MS <sub>9,10</sub>	-0.536	0.018
SDS <sub>9,10</sub>	2.247	0.127
MS <sub>10,10</sub>	-1.000	0.000
SDS <sub>10,10</sub>	0.001	0.038

Table 42: Estimates: Measurement system -Skills in 2012

Parameter	Estimate	Standard Error
MS <sub>1_2</sub>	1.000	0.000
SDS <sub>1_2</sub>	2.776	0.063
MS <sub>2_2</sub>	0.929	0.076
SDS <sub>2_2</sub>	3.126	0.046
MS <sub>3_2</sub>	1.106	0.095
SDS <sub>3_2</sub>	2.939	0.019
MS <sub>4_2</sub>	1.041	0.007
SDS <sub>4_2</sub>	2.985	0.016
MS <sub>5_2</sub>	0.997	0.017
SDS <sub>5_2</sub>	3.598	0.039
MS <sub>6_2</sub>	1.095	0.013
SDS <sub>6_2</sub>	2.310	0.017
MS <sub>7_2</sub>	1.093	0.039
SDS <sub>7_2</sub>	2.850	0.082
MS <sub>8_2</sub>	1.102	0.088
SDS <sub>8_2</sub>	2.476	0.009
MS <sub>9_2</sub>	0.965	0.018
SDS <sub>9_2</sub>	3.088	0.007
MS <sub>10_2</sub>	1.223	0.010
SDS <sub>10_2</sub>	0.004	0.072
MS <sub>11_2</sub>	1.108	0.007
SDS <sub>11_2</sub>	4.848	0.037

Table 43: Estimates: Measurement system -Skills at birth

Parameter	Estimate	Standard Error
MS <sub>1<sub>BIRTH</sub></sub>	-0.492	0.248
SDS <sub>1<sub>BIRTH</sub></sub>	0.077	0.057
MS <sub>2<sub>BIRTH</sub></sub>	-0.394	0.205
SDS <sub>2<sub>BIRTH</sub></sub>	0.055	0.037
MS <sub>3<sub>BIRTH</sub></sub>	-0.237	0.216
SDS <sub>3<sub>BIRTH</sub></sub>	0.066	0.079
MS <sub>4<sub>BIRTH</sub></sub>	-0.632	0.366
SDS <sub>4<sub>BIRTH</sub></sub>	0.111	0.100
MS <sub>5<sub>BIRTH</sub></sub>	-0.140	0.105
SDS <sub>5<sub>BIRTH</sub></sub>	0.030	0.030
MS <sub>6<sub>BIRTH</sub></sub>	-0.549	0.354
SDS <sub>6<sub>BIRTH</sub></sub>	0.098	0.079
MS <sub>7<sub>BIRTH</sub></sub>	-0.093	0.009
SDS <sub>7<sub>BIRTH</sub></sub>	0.021	0.075
MS <sub>8<sub>BIRTH</sub></sub>	-0.350	0.186
SDS <sub>8<sub>BIRTH</sub></sub>	0.082	0.028
MS <sub>9<sub>BIRTH</sub></sub>	-0.352	0.260
SDS <sub>9<sub>BIRTH</sub></sub>	0.039	0.023
MS <sub>10<sub>BIRTH</sub></sub>	-3.068	1.894
SDS <sub>10<sub>BIRTH</sub></sub>	0.631	0.418
MS <sub>11<sub>BIRTH</sub></sub>	-0.059	0.006
SDS <sub>11<sub>BIRTH</sub></sub>	0.007	0.058
MS <sub>12<sub>BIRTH</sub></sub>	-0.165	0.055
SDS <sub>12<sub>BIRTH</sub></sub>	0.022	0.020
MS <sub>13<sub>BIRTH</sub></sub>	-1.000	0.000
SDS <sub>13<sub>BIRTH</sub></sub>	0.090	0.106
MS <sub>14<sub>BIRTH</sub></sub>	-0.709	0.447
SDS <sub>14<sub>BIRTH</sub></sub>	0.076	0.035
MS <sub>15<sub>BIRTH</sub></sub>	-0.124	0.086
SDS <sub>15<sub>BIRTH</sub></sub>	0.017	0.064
MS <sub>16<sub>BIRTH</sub></sub>	-0.114	0.101
SDS <sub>16<sub>BIRTH</sub></sub>	0.014	0.023
MS <sub>17<sub>BIRTH</sub></sub>	-0.107	0.025
SDS <sub>17<sub>BIRTH</sub></sub>	0.000	0.035
MS <sub>18<sub>BIRTH</sub></sub>	-0.125	0.058
SDS <sub>18<sub>BIRTH</sub></sub>	0.000	0.041
MS <sub>19<sub>BIRTH</sub></sub>	-0.185	0.055
SDS <sub>19<sub>BIRTH</sub></sub>	0.000	0.039
MS <sub>20<sub>BIRTH</sub></sub>	-0.059	0.052
SDS <sub>20<sub>BIRTH</sub></sub>	0.000	0.005
MS <sub>21<sub>BIRTH</sub></sub>	-0.415	0.193
SDS <sub>21<sub>BIRTH</sub></sub>	0.078	0.043
MS <sub>22<sub>BIRTH</sub></sub>	0.080	0.012
SDS <sub>22<sub>BIRTH</sub></sub>	0.199	0.177
MS <sub>23<sub>BIRTH</sub></sub>	0.026	0.003
SDS <sub>23<sub>BIRTH</sub></sub>	0.203	0.065

Table 44: Estimates: Measurement system -Skills of Primary Caregiver

Parameter	Estimate	Standard Error
$MS_{1,PG}$	0.648	0.074
$SDS_{1,PG}$	1.788	0.046
$MS_{2,PG}$	0.907	0.070
$SDS_{2,PG}$	1.827	0.104
$MS_{3,PG}$	0.698	0.020
$SDS_{3,PG}$	1.705	0.032
$MS_{4,PG}$	1.000	0.000
$SDS_{4,PG}$	1.655	0.138
$MS_{5,PG}$	0.894	0.033
$SDS_{5,PG}$	1.741	0.060
$MS_{6,PG}$	-1.039	0.038
$SDS_{6,PG}$	1.652	0.053
$MS_{7,PG}$	0.840	0.002
$SDS_{7,PG}$	1.627	0.072

Table 45: Estimates: Measurement system -Pareto weight

Parameter	Estimate	Standard Error
$MS_{1BARG}$	-0.199	0.016
$SDS_{1BARG}$	0.570	0.152
$MS_{2BARG}$	0.081	0.039
$SDS_{2BARG}$	0.586	0.089
$MS_{3BARG}$	-0.075	0.011
$SDS_{3BARG}$	0.591	0.063
$MS_{4BARG}$	0.017	0.015
$SDS_{4BARG}$	0.560	0.052
$MS_{5BARG}$	0.113	0.031
$SDS_{5BARG}$	0.591	0.054
$MS_{6BARG}$	-0.134	0.091
$SDS_{6BARG}$	0.587	0.077
$MS_{7BARG}$	0.106	0.007
$SDS_{7BARG}$	0.559	0.070
$MS_{8BARG}$	-0.007	0.014
$SDS_{8BARG}$	0.572	0.083
$MS_{9BARG}$	0.092	0.047
$SDS_{9BARG}$	0.583	0.074
$MS_{10BARG}$	-0.026	0.013
$SDS_{10BARG}$	0.571	0.059
$MS_{11BARG}$	0.015	0.026
$SDS_{11BARG}$	0.027	0.032
$MS_{12BARG}$	0.041	0.021
$SDS_{12BARG}$	0.011	0.055
$MS_{13BARG}$	0.601	0.104
$SDS_{13BARG}$	0.550	0.049
$MS_{14BARG}$	-0.502	0.135
$SDS_{14BARG}$	0.464	0.072
$MS_{15BARG}$	0.266	0.006
$SDS_{15BARG}$	0.138	0.007
$MS_{16BARG}$	-0.717	0.076
$SDS_{16BARG}$	0.552	0.097
$MS_{17BARG}$	1.000	0.145
$SDS_{17BARG}$	0.173	0.033
$MS_{18BARG}$	0.561	0.076
$SDS_{18BARG}$	0.061	0.012

Table 46: Estimates: Measurement system -Investments 2010

Parameter	Estimate	Standard Error
$MS_{1_{INV,10}}$	0.134	0.207
$SDS_{1_{INV,10}}$	0.200	0.132
$MS_{2_{INV,10}}$	1.000	0.000
$SDS_{2_{INV,10}}$	2.432	1.344
$MS_{3_{INV,10}}$	0.416	0.236
$SDS_{3_{INV,10}}$	0.670	0.386
$MS_{4_{INV,10}}$	0.353	0.159
$SDS_{4_{INV,10}}$	0.520	0.332
$MS_{5_{INV,10}}$	0.051	0.068
$SDS_{5_{INV,10}}$	0.066	0.019
$MS_{6_{INV,10}}$	0.045	0.009
$SDS_{6_{INV,10}}$	0.186	0.100
$MS_{7_{INV,10}}$	0.112	0.035
$SDS_{7_{INV,10}}$	0.262	0.191
$MS_{8_{INV,10}}$	0.081	0.011
$SDS_{8_{INV,10}}$	0.289	0.166

Table 47: Estimates: Measurement system -Investments 2012

Parameter	Estimate	Standard Error
MS <sub>1<sub>INV,12</sub></sub>	0.025	0.000
SDS <sub>1<sub>INV,12</sub></sub>	0.898	0.087
MS <sub>2<sub>INV,12</sub></sub>	0.029	0.033
SDS <sub>2<sub>INV,12</sub></sub>	1.021	0.057
MS <sub>3<sub>INV,12</sub></sub>	0.002	0.043
SDS <sub>3<sub>INV,12</sub></sub>	0.943	0.014
MS <sub>4<sub>INV,12</sub></sub>	0.021	0.037
SDS <sub>4<sub>INV,12</sub></sub>	0.977	0.122
MS <sub>5<sub>INV,12</sub></sub>	0.036	0.043
SDS <sub>5<sub>INV,12</sub></sub>	1.030	0.120
MS <sub>6<sub>INV,12</sub></sub>	0.079	0.007
SDS <sub>6<sub>INV,12</sub></sub>	0.966	0.116
MS <sub>7<sub>INV,12</sub></sub>	-0.000	0.033
SDS <sub>7<sub>INV,12</sub></sub>	1.028	0.027
MS <sub>8<sub>INV,12</sub></sub>	0.037	0.067
SDS <sub>8<sub>INV,12</sub></sub>	0.550	0.111
MS <sub>9<sub>INV,12</sub></sub>	0.013	0.038
SDS <sub>9<sub>INV,12</sub></sub>	0.856	0.079
MS <sub>10<sub>INV,12</sub></sub>	0.030	0.010
SDS <sub>10<sub>INV,12</sub></sub>	0.965	0.137
MS <sub>11<sub>INV,12</sub></sub>	0.052	0.046
SDS <sub>11<sub>INV,12</sub></sub>	1.053	0.164
MS <sub>12<sub>INV,12</sub></sub>	0.256	0.014
SDS <sub>12<sub>INV,12</sub></sub>	0.467	0.093
MS <sub>13<sub>INV,12</sub></sub>	0.456	0.064
SDS <sub>13<sub>INV,12</sub></sub>	0.986	0.075
MS <sub>14<sub>INV,12</sub></sub>	0.261	0.035
SDS <sub>14<sub>INV,12</sub></sub>	0.993	0.198
MS <sub>15<sub>INV,12</sub></sub>	0.002	0.008
SDS <sub>15<sub>INV,12</sub></sub>	0.002	0.030
MS <sub>16<sub>INV,12</sub></sub>	0.379	0.034
SDS <sub>16<sub>INV,12</sub></sub>	0.709	0.123
MS <sub>17<sub>INV,12</sub></sub>	0.099	0.061
SDS <sub>17<sub>INV,12</sub></sub>	0.130	0.089
MS <sub>18<sub>INV,12</sub></sub>	0.408	0.058
SDS <sub>18<sub>INV,12</sub></sub>	1.126	0.070
MS <sub>19<sub>INV,12</sub></sub>	1.000	0.000
SDS <sub>19<sub>INV,12</sub></sub>	3.331	0.283
MS <sub>20<sub>INV,12</sub></sub>	-0.086	0.029
SDS <sub>20<sub>INV,12</sub></sub>	1.108	0.119
MS <sub>21<sub>INV,12</sub></sub>	-0.080	0.074
SDS <sub>21<sub>INV,12</sub></sub>	0.980	0.112



Table 48: Estimates: Measurement system -Parental effort 2010

Parameter	Estimate	Standard Error
$MS_{1_{EF,10}}$	0.368	0.018
$SDS_{1_{EF,10}}$	1.101	0.066
$MS_{2_{EF,10}}$	0.280	0.012
$SDS_{2_{EF,10}}$	0.887	0.100
$MS_{3_{EF,10}}$	0.212	0.020
$SDS_{3_{EF,10}}$	0.325	0.061
$MS_{4_{EF,10}}$	0.280	0.059
$SDS_{4_{EF,10}}$	1.100	0.131
$MS_{5_{EF,10}}$	0.311	0.052
$SDS_{5_{EF,10}}$	0.426	0.133
$MS_{6_{EF,10}}$	1.000	0.000
$SDS_{6_{EF,10}}$	1.178	0.039

Table 49: Estimates: Measurement system -Parental effort 2012

Parameter	Estimate	Standard Error
$MS_{1_{EF,12}}$	0.370	0.012
$SDS_{1_{EF,12}}$	1.759	0.038
$MS_{2_{EF,12}}$	0.358	0.058
$SDS_{2_{EF,12}}$	1.698	0.095
$MS_{3_{EF,12}}$	0.498	0.023
$SDS_{3_{EF,12}}$	1.885	0.004
$MS_{4_{EF,12}}$	0.272	0.048
$SDS_{4_{EF,12}}$	1.720	0.079
$MS_{5_{EF,12}}$	0.239	0.060
$SDS_{5_{EF,12}}$	1.661	0.035
$MS_{6_{EF,12}}$	0.565	0.068
$SDS_{6_{EF,12}}$	1.853	0.144
$MS_{7_{EF,12}}$	0.524	0.032
$SDS_{7_{EF,12}}$	1.779	0.149
$MS_{8_{EF,12}}$	0.448	0.051
$SDS_{8_{EF,12}}$	1.814	0.017
$MS_{9_{EF,12}}$	0.395	0.037
$SDS_{9_{EF,12}}$	1.955	0.045
$MS_{10_{EF,12}}$	0.849	0.083
$SDS_{10_{EF,12}}$	1.397	0.139
$MS_{11_{EF,12}}$	0.895	0.004
$SDS_{11_{EF,12}}$	1.331	0.013
$MS_{12_{EF,12}}$	0.421	0.001
$SDS_{12_{EF,12}}$	1.646	0.103
$MS_{13_{EF,12}}$	1.007	0.007
$SDS_{13_{EF,12}}$	0.042	0.010
$MS_{14_{EF,12}}$	1.000	0.000
$SDS_{14_{EF,12}}$	0.035	0.053

## 11.4 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  $rr=1\dots RR$ :
    - 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  $rr=1\dots RR$ :
    - i. Draw  $\theta_t$  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  $rr=1\dots RR$ 
    - 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  $rr=1\dots RR$ 
    - 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.

## 11.5 Smoothing distribution

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

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

$$p(K_t | O_{0:2}) \quad (83)$$

where we basically condition on all the measures we have. Note that we can write Equation 83 as:

$$p(K_t | O_{0:2}) = p(K_t | O_{0:t}) \int \left( \frac{p(K_{t+1} | O_{0:2}) p(K_{t+1} | \theta_t)}{\int p(K_{t+1} | \theta_t) p(K_1 | O_{0:t}) dK_t} \right) dK_{t+1} \quad (84)$$

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

$$\hat{p}(K_t | O_{0:2}) = \sum_{rr=1}^{RR} w_{t|T}^{(rr)} \delta_{K_t^{(rr)}}(K_t) \quad (85)$$

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

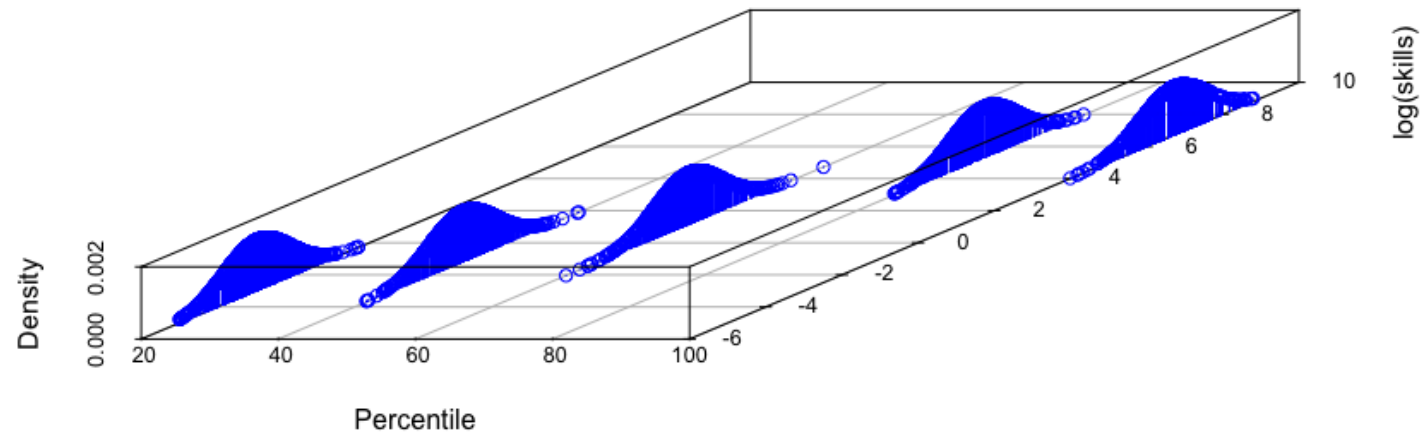
$$w_{t|T}^{(mm)} = w_t^{(mm)} \left[ \sum_{rr=1}^{RR} w_{t+1|T}^{(rr)} \left( \frac{p(K_{t+1}^{(rr)} | K_t^{(mm)})}{\sum_{kk=1}^{KK} w_t^{(kk)} p(K_{t+1}^{(rr)} | K_t^{(kk)})} \right) \right] \quad (86)$$

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  $rr = 1 \dots RR$
3. For  $t=1,0$  define  $w_{t|2}^{(mm)} = w_t^{(mm)} \left[ \sum_{rr=1}^{RR} w_{t+1|2}^{(rr)} \left( \frac{p(x_{t+1}^{(rr)} | x_t^{(mm)})}{\sum_{kk=1}^{KK} w_t^{(kk)} p(x_{t+1}^{(rr)} | x_t^{(kk)})} \right) \right]$

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



The distribution of  $\log(\text{skills})$  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 12

## 11.6 Signal to Noise Ratio

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

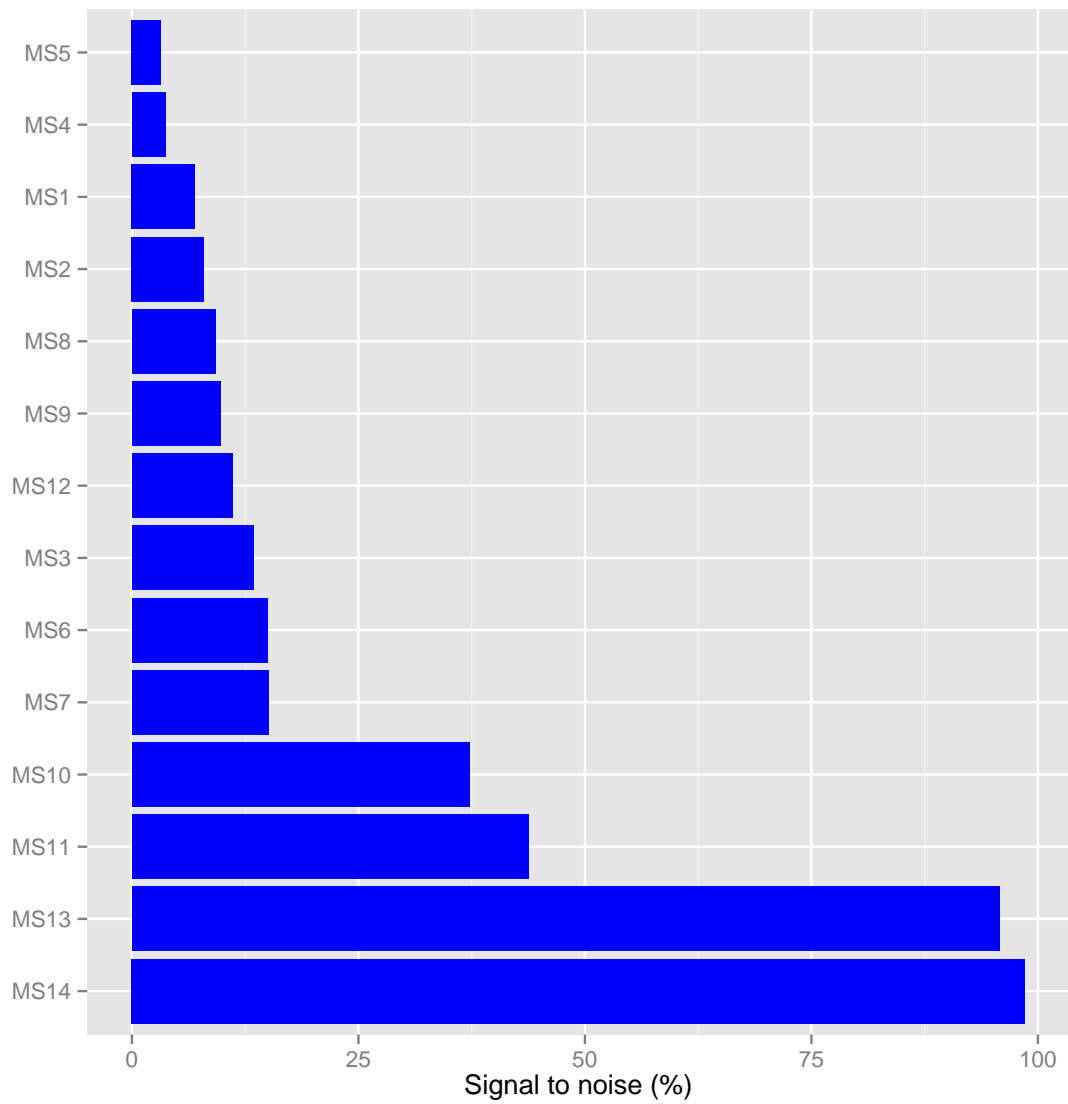


Figure 16: Signal to noise ratio. Father's effort (2012)

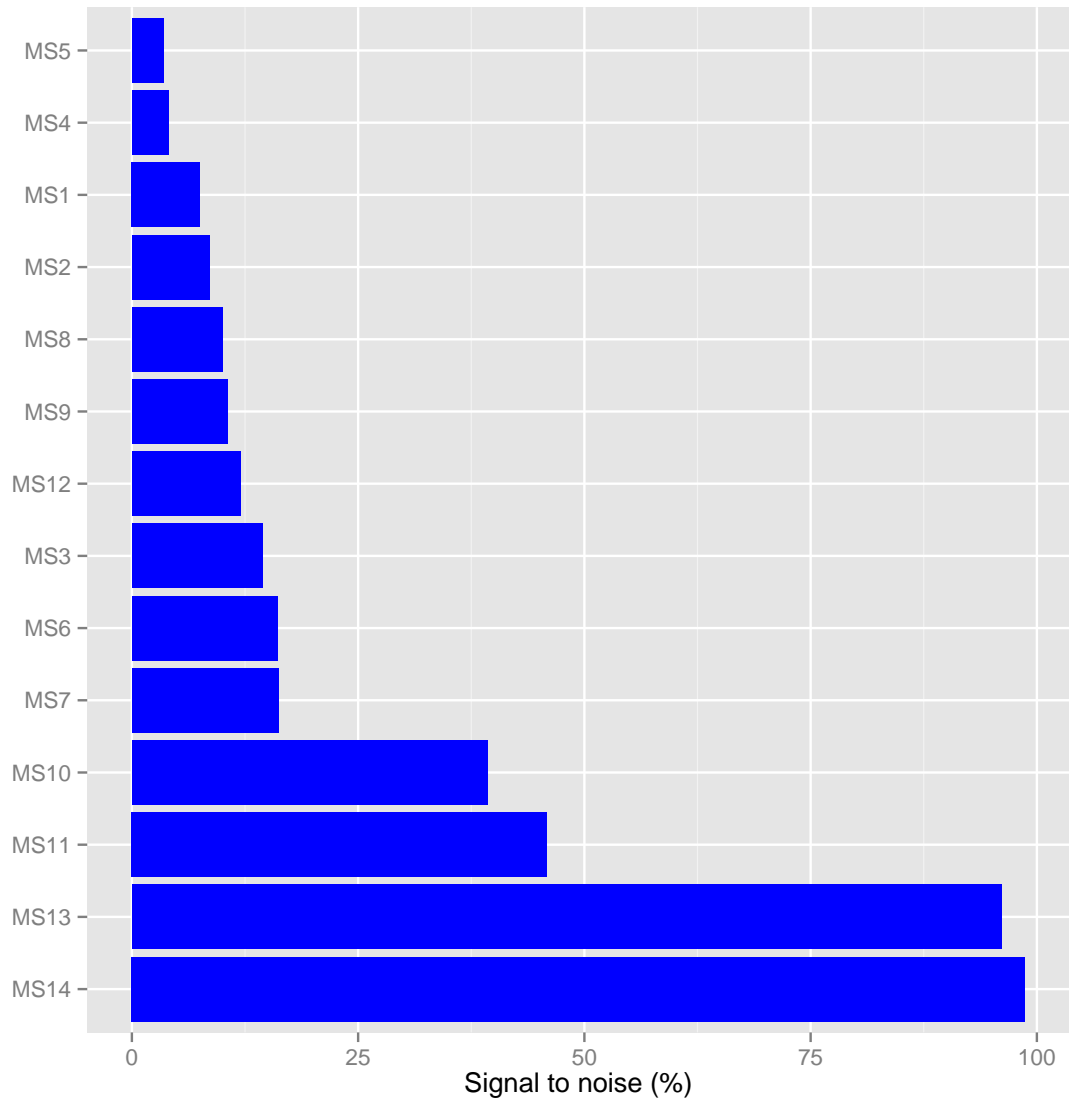




Figure 17: Signal to noise ratio. Mother's effort (2010)

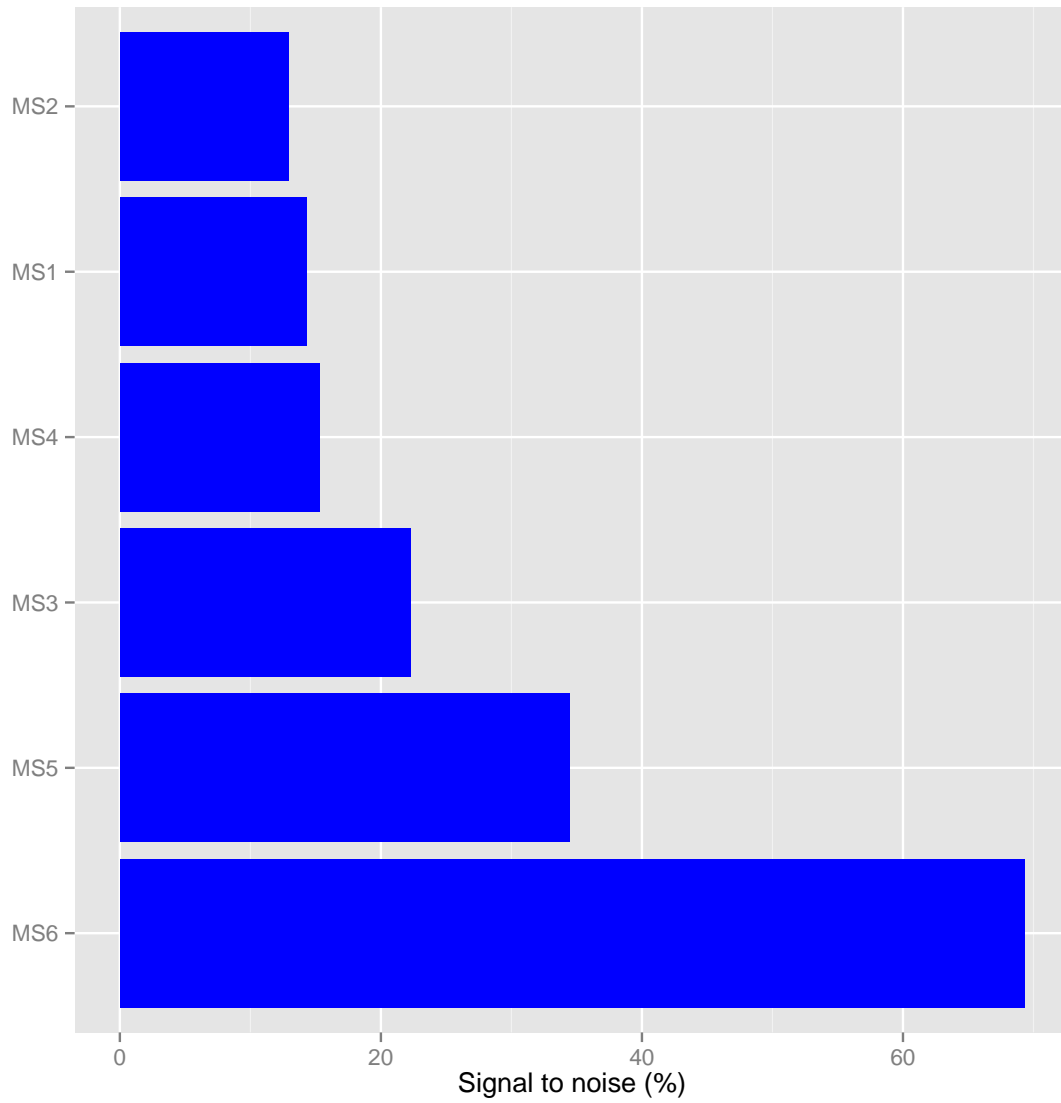


Figure 18: Signal to noise ratio. Father's effort (2010)

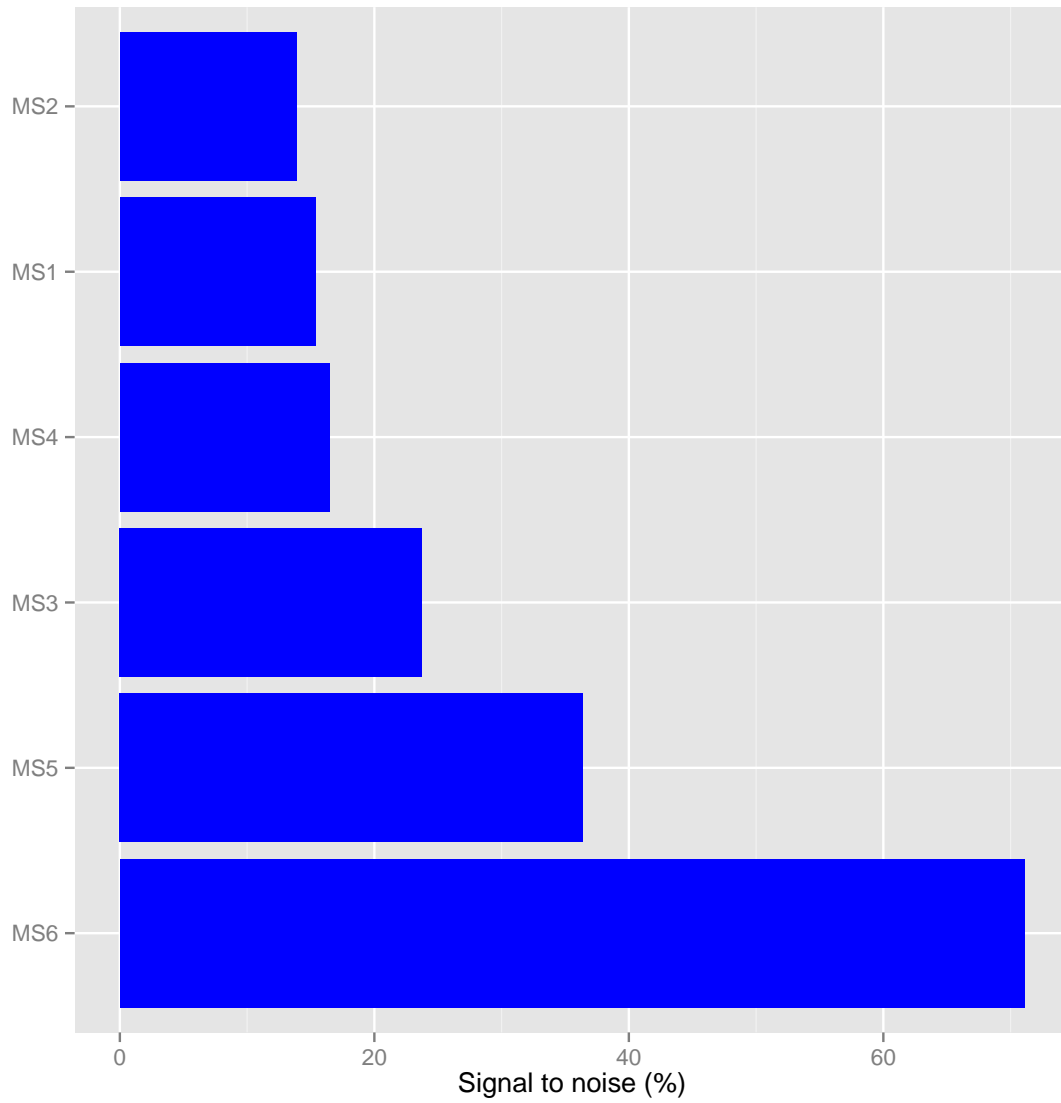


Figure 19: Signal to noise ratio. Monetary Investment (2010)

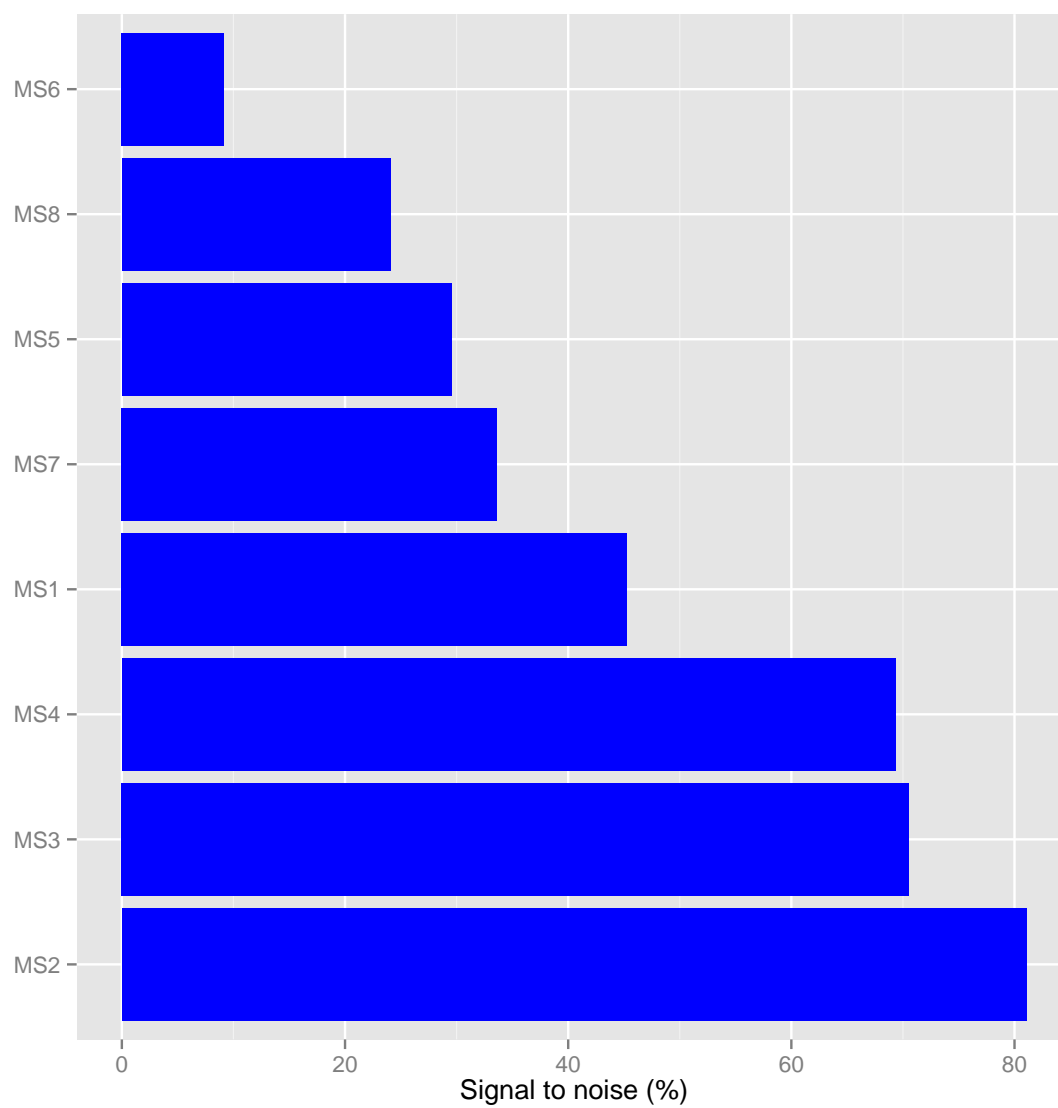


Figure 20: Signal to noise ratio. Monetary Investment (2012)

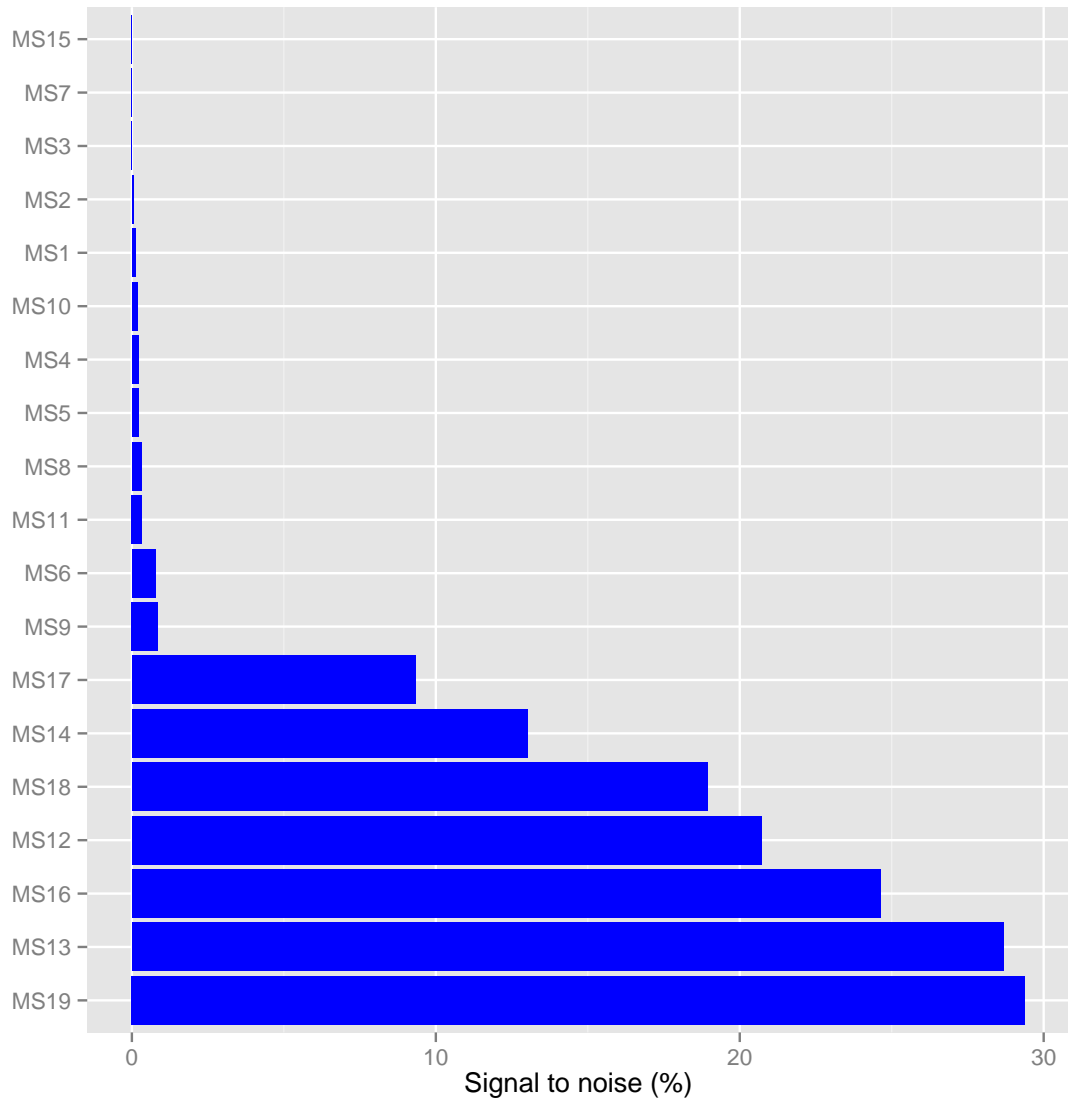


Figure 21: Signal to noise ratio. Birth Outcomes

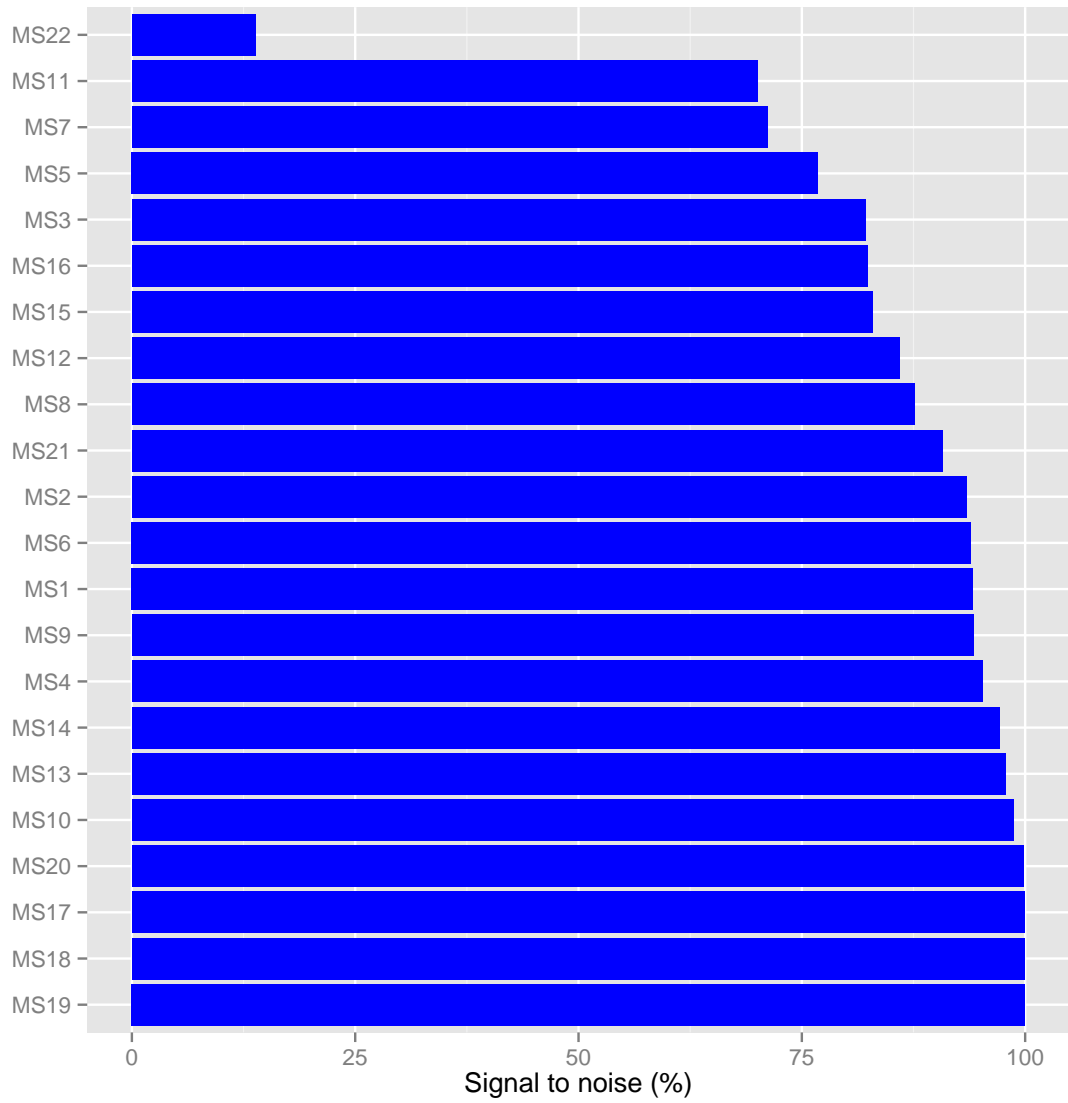


Figure 22: Signal to noise ratio. Skills (2010)

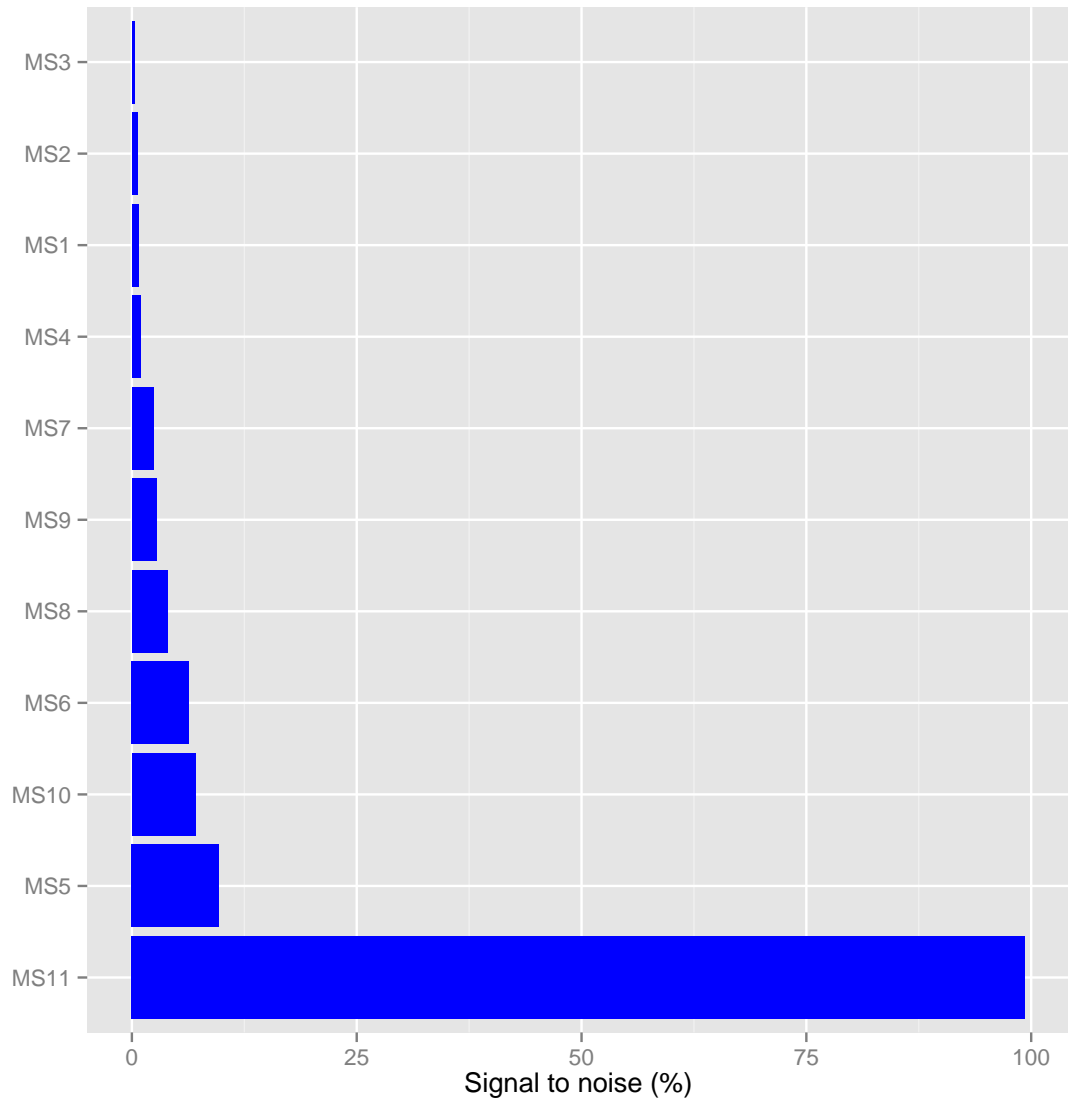


Figure 23: Signal to noise ratio. Skills (2012)

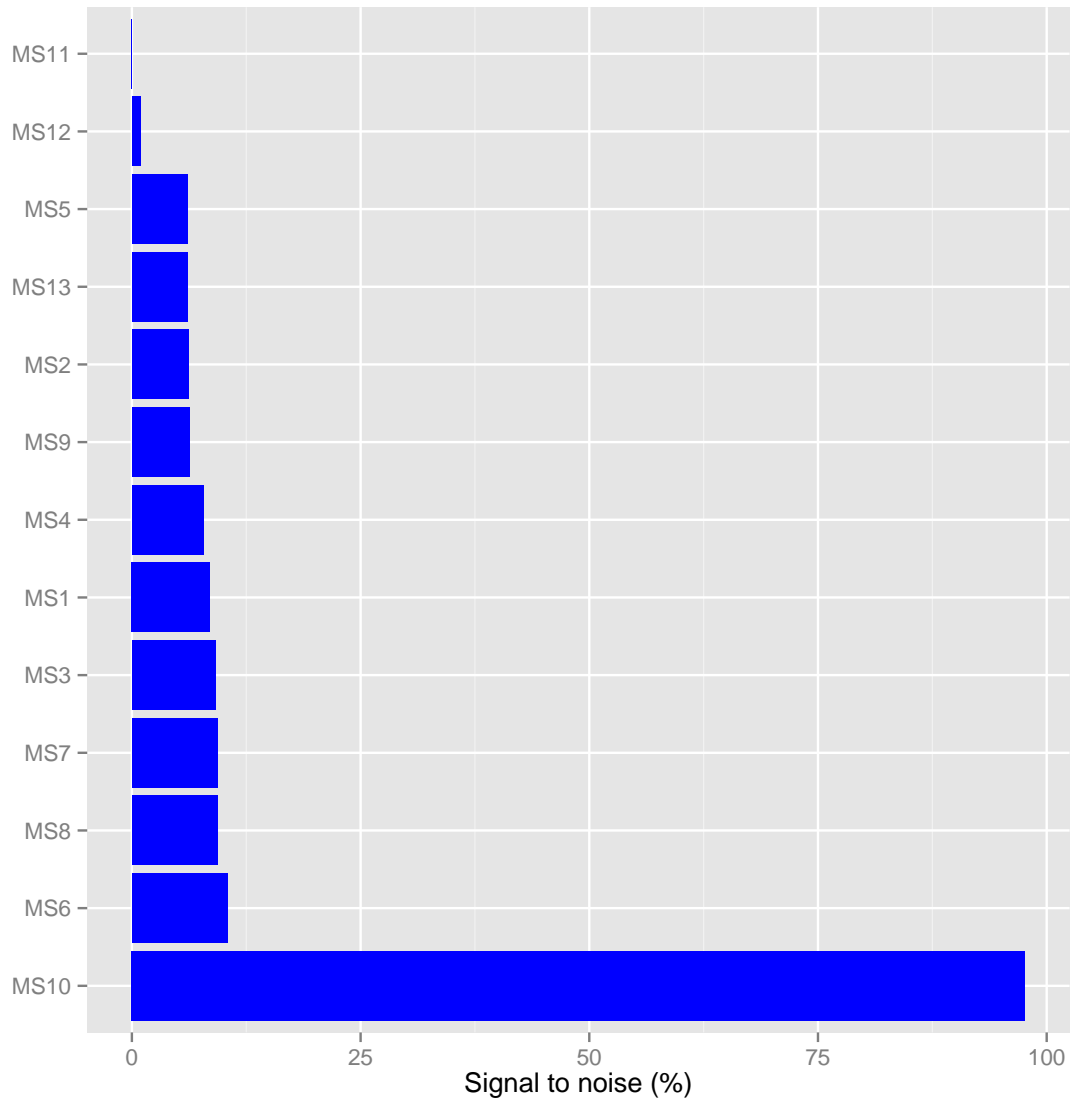


Figure 24: Signal to noise ratio. Bargaining power

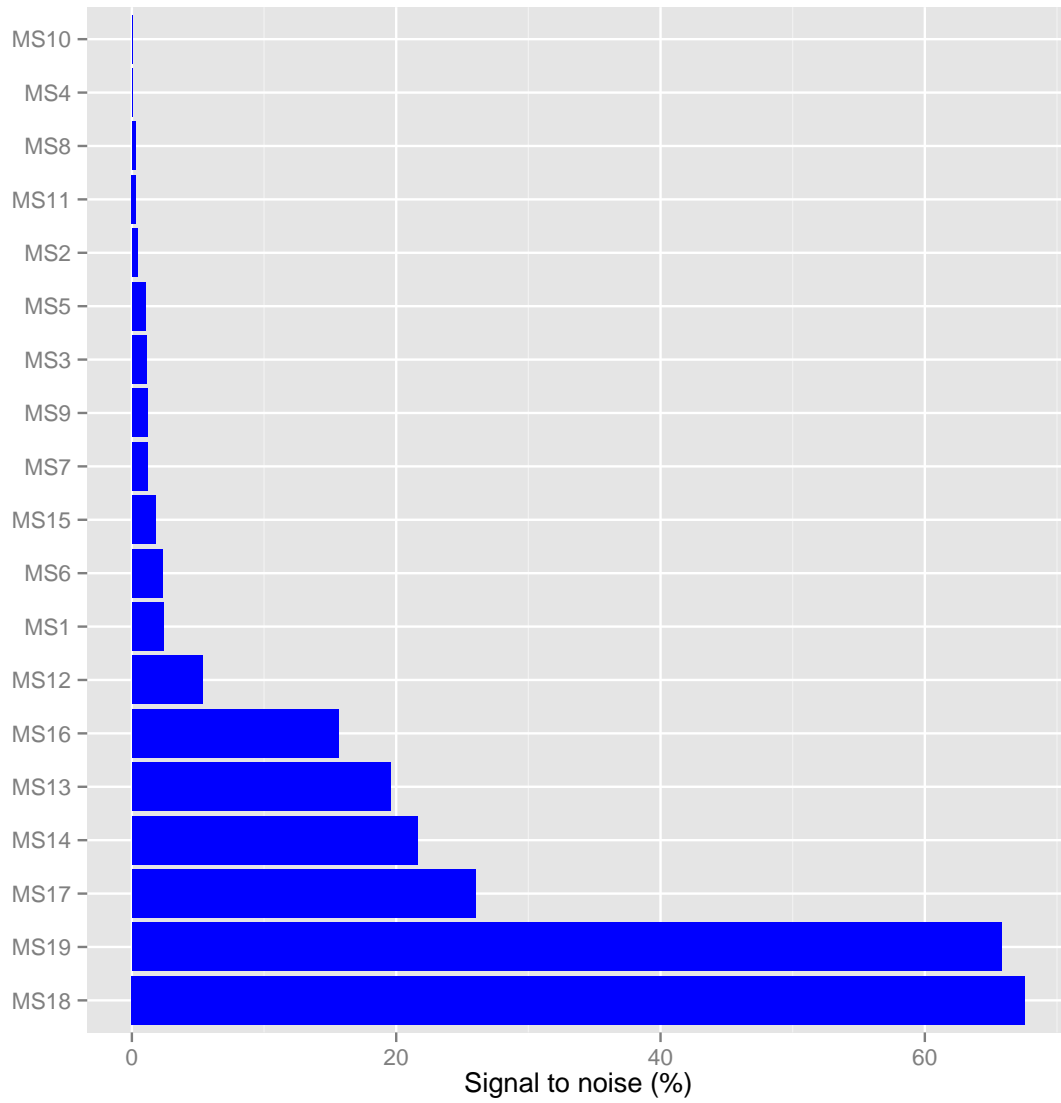
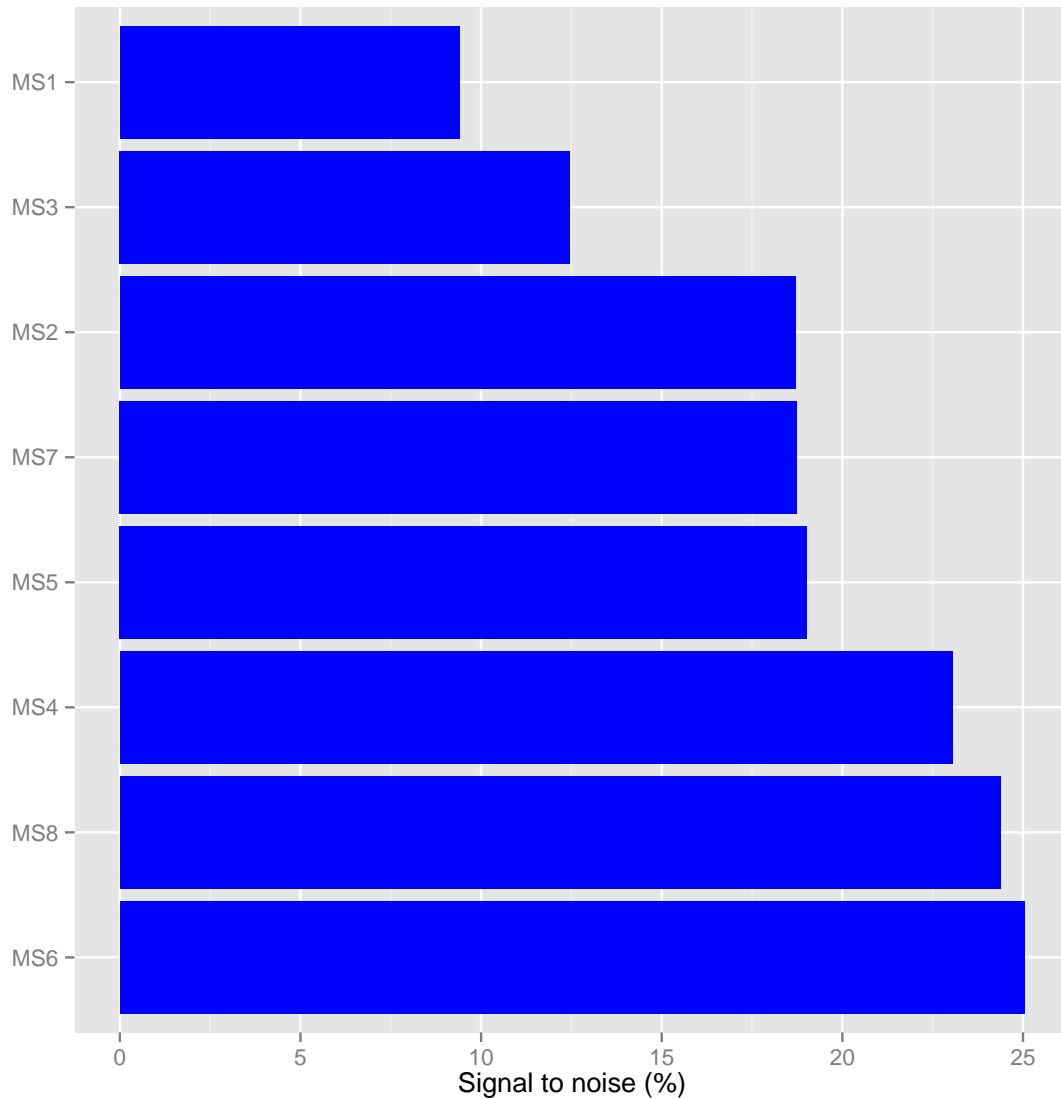




Figure 25: Signal to noise ratio. Primary Caregiver Skills



### 11.7 Cash Transfer Programs in Chile

The basic program through which poor families receive cash transfers from the central government is the “Unique Family Subsidy”<sup>16</sup>. Such program established a monthly transfer of \$14,340

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<sup>16</sup>Subsidio Unico familiar in Spanish.

CLP in 2012, for a family in conditions of vulnerability<sup>17</sup> with one child<sup>18</sup>. 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<sup>19</sup>.

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 “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 annually 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.

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<sup>17</sup>The condition of vulnerability corresponds to a score below 11.734 in the “Ficha de Protección Social”. Approximately 40% of Chilean families lie below this threshold

<sup>18</sup>The \$14,340 CLP were generated by the mother and the child, each generating a transfer of \$7,170 CLP.

<sup>19</sup>The transfer scheme consisted of \$7,179 CLP 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.