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

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October 22, 2017

Abstract

There is extensive evidence showing the importance of early childhood development for adult life outcomes. However, we have no certainty about what are the most cost-effective policies to increase skills for children in disadvantage. In this paper, I develop and estimate a technology of skill formation nested within a collective model of household behavior to evaluate the effect of various policy counterfactuals. The model incorporates different channels of parental investments in children such as time investments, material investments, and childcare services. The estimated model is used to assess the effect of three policies on children's skills: cash transfers, daycare subsidies, and subsidies for children-specific goods. The results of the estimation exercise allow me to incorporate how parental investments respond to policy counterfactuals. I find that subsidies to children-specific goods are more effective per dollar than cash transfers or daycare subsidies.

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1 Introduction

Research in medicine, psychology and economics shows that skills shaped during the first years of life have significant consequences for adult life outcomes.[1] This has motivated a large amount of research in economics aimed at understanding the skill formation process. The results of these studies allow a better understanding of the key inputs that promote skills in young children.[2] For instance, they showed that parenting and general family environment are among the most relevant inputs in the production of skills (J. Heckman & Mosso, 2014; Schoellman, 2014). Moreover, the literature has provided evidence suggesting that gaps in skills between rich and poor children emerge very early in life, even before they start their formal education (Duncan & Magnuson, 2013; Schady et al., 2015; Nelson & Sheridan, 2011).

These facts have motivated a large number of policies aimed at enhancing the skills of children in disadvantage. However, we still have no certainty about what are the most cost-effective policies to close the gaps of skills between rich and poor children. Furthermore, although the question of what are the key inputs and the most sensitive periods of child skills formation has been asked previously in the literature[3], family investments have been proved to be key inputs in the skills production function, and they might react as a consequence of introducing new policies. The goal of this paper is to asses which policies are most effective to close the gaps in skills between rich and poor children, taking into account that family investments change as a consequence of public policy.

To analyze how early childhood policies affect resources allocated to children and skill formation, I develop and estimate a skill production function nested within a collective model of household behavior. In the economic model, parents -who can have potentially different preferences- care about the skills of their child and need to make investments to increase the stock of skills. Such investments can take the form of time investments -such as playing, reading, or signing to the child-, material investments -toys, puzzles, music or adequate food, among others- and childcare services. I use a novel dataset from Chile to estimate the parameters of the

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

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

[3] See, for example, Todd and Wolpin (2007), Cunha et al. (2010), Chetty et al. (2011), and J. Heckman and Mosso (2014) for a review.

model. The results of the estimation exercise are used to simulate the effect that three different types of policies have on the skills of children: cash transfers, childcare subsidies and subsidies for child-specific investments. The results show that subsidizing material investments for children is the most effective way to promote skills for children in conditions of disadvantage.

There are few papers estimating structural models of household behavior and child outcomes with the goal of understanding how family behavior affects child skill formation (Bernal, 2008; Del Boca, Flinn, & Wiswall, 2014; Gayle, Golan, & Soytas, 2015). This is the first paper that empirically evaluates a collective model of household behavior and child investments incorporating decisions of time investments, monetary investments and childcare-preschool services. Taking into account these three channels of investments is relevant since we are able to asses how each policy affects different dimensions of parental investments in their children. The results of this paper allow us to have a better idea of what policies are most effective in promoting skills of young children and the mechanisms through which each policy affects such a process.

By modeling household behavior through the collective approach, parents are allowed to have different preferences. Incorporating the collective model of household behavior in the process of skills formation for children is a relevant contribution for various reasons. First, modeling household behavior through the collective approach has proven to result in better empirical predictions than the unitary framework (Chiappori & Donni, 2009). Second, from a policy perspective, it is common to see interventions targeting individual household members. For instance, most cash transfer programs in developing countries state as an explicit condition that, in households with children, mothers should be the sole recipients of such subsidies (Fiszbein, Schady, & Ferreira, 2009). It is often argued that mothers have stronger preferences for meeting the needs of children and therefore cash in the hands of mothers translates into better child outcomes (Blundell, Chiappori, & Meghir, 2005). Moreover, the empirical regularity that there is a positive correlation between women's empowerment and child development (Haddad, Hoddinott, Alderman, et al., 1997) cannot be explained by considering the household as a single entity with one utility function. The collective approach provides a framework that allows us to assess the extent to which targeting individual members as beneficiaries of policies, such as cash transfers, actually have consequences on child development. Furthermore, it provides an ideal framework to test the effects of female empowerment on child development.

The dataset used in this paper is the Early Childhood Longitudinal Survey from Chile (ECLS). This dataset contains detailed information regarding the skill formation process in children and allows me to overcome some empirical limitations that the literature has previously faced. For instance, studies have shown that parental skills largely determine children's skills (J. Heckman & Mosso, 2014). By having information on parental IQ tests and personality assessments, I am able to incorporate parental skills into my estimation strategy. Additionally, we know that there is a multiplicity of skills that are relevant to determining adult life outcomes (Cunha et al., 2010). I incorporate multiple measures of skills across various dimensions, such as motor, communication, cognitive and behavioral abilities in children. Additionally, the dataset contains detailed information about the time and material investments that parents make in their children, such as the weekly frequency with which each parent reads to the child, or the availability of toys, books for children and the consumption of different types of foods. This allows me to incorporate the quantity and quality of investments that families make in their children.

Moreover, this is the first paper in the literature of household choices and child development that estimates a technology of skill formation through a dynamic latent-factor approach a-là Cunha et al. (2010). This allows me to obtain non-parametric identification of the skill production technology by using a large number of skill measures. Because of that, the results of the estimation are less sensitive to the specific parametric form assumed for the skill formation technology, and the bias arising from measurement error is reduced, making the results more robust. This, along with the fact that a latent factor structure can be interpreted as unobserved heterogeneity (Carneiro, Hansen, & Heckman, 2003) and potentially improves the accuracy of the estimates, has made factor analysis a popular tool to get accurate estimates of the skill production function (Cunha et al., 2010; Cunha & Heckman, 2008; J. J. Heckman, Stixrud, & Urzua, 2006). This paper is the first to estimate the production function of skills via a latent-factor approach, nested within a collective model of household behavior. This paper also makes a methodological contribution to the estimation of dynamic microeconomic models with unobserved and continuous state variables. By implementing an efficient simulation-based estimator using particle filtering techniques (Murphy, 2012; Creal, 2012), I propose a feasible computational approach for dealing with the high dimensionality integration problem that arises in such models.

In this paper, I propose a new estimation strategy for collective models of household behavior. The collective model of household behavior assumes that parents have different preferences and the final allocation of resources is a Pareto efficient outcome. The extent to which the final outcome follows preferences of each member depends on the Pareto weight, or bargaining power, of each member. Traditionally, empirical applications of the collective model use data on goods that are assumed to be of private consumption such as gender specific clothing or personal care items (Cherchye, De Rock, & Vermeulen, 2012; Blundell et al., 2005). This approach imposes certain assumptions on the behavior of families such as that one member does not care about the consumption level of other members on such goods. For instance, a husband would be indifferent about the consumption level on personal care of his wife. Additionally, it assumes that the intra-household bargaining process can be fully explained by observing the consumption of such items. This approach fails in the presence of measurement error or when there are more elements in the bargaining process in addition to the goods observed to the econometrician. Rather than using information on private consumption, I use answers to questionnaires related to female empowerment and gender roles within the household, such as who makes decisions about how to spend the income. Through a latent factor approach estimation, I use these answers as noisy measures of the bargaining power of each member. This approach allows for unobserved heterogeneity, measurement error, and does not rely on the assumption that the whole bargaining process is explained by the consumption of specific elements considered to be of private consumption.

The data from test scores show significant large gaps in skills between rich and poor children at age 5. The skill gap between children in the lowest quintile of the income distribution and children in the highest quintile, is in between 0.3 and 0.7 standard deviations in tests measuring cognitive abilities, socio-emotional development, and vocabulary skills, among others. These inequalities are mostly explained by differences in parental skills and monetary investments. Additionally, the model parameter estimates show that fathers' time spent with children is 50% as productive as mothers' time and that mothers have stronger preferences for children.

When analyzing which policy is more effective for child skills formation, it is not clear *a priori* which one would be more effective: cash transfers, childcare subsidies, or subsidies for material investments. Cash transfers allow parents to spend the money freely: there is no guarantee that they will do it in the way that is most effective for children, as they might decide to spend it on elements of private consumption. Cash transfers could also increase time investments from parents, depending on the extent to which cash transfers decrease labor force participation. Childcare subsidies could potentially expose children to a better suited environment for skill promotion. However, there is evidence from Latin America pointing out that such centers can have negative effects on child skill formation (Behrman, Cheng, & Todd, 2004; Bernal, Fernández, Flórez, Gaviria, et al., 2009; Rosero Moncayo, Oosterbeek, et al., 2011). Childcare subsidies could also increase female labor force participation, further decreasing the amount of time that parents spend with their children. Finally, subsidies to child investments are guaranteed to end up being used for skill formation purposes. However, it is unclear how effective they are when compared to other inputs such as parental time or childcare services.

Regarding the targeting aspect of cash transfers, the extent to which children would benefit more by having mothers as beneficiaries is also unclear. This depends on how effective cash transfers are in empowering women in households, how different are preferences for child skills between parents, and also on the marginal willingness to pay for skills from each parent. This last point is related to the fact that both parents need to make private investments of time and money for child skills. However, skills are ultimately a public good, since both parents get benefits from it. The extent to which each member contributes to skill formation in children depends on the marginal willingness to pay. For instance, even if fathers cared less for their children, they might be at a relatively low level of marginal utility of consumption such that for each additional dollar earned, most of it would end up in children investment.

The results of the counterfactual policy analysis suggest that, taking into account the aforementioned features about the three different programs considered, subsidies for child-specific investments are the most effective way to promote child development. At any point, they provide the highest marginal return, implying that the optimal policy would not be a mixture between programs but rather devoting all resources to such a policy.

The remainder of this article is structured as follows: In section 2 I introduce a collective model of household behavior and child skill formation. I describe the data in Section 3. I discuss the estimation and identification of the economic model in Section 4. The main results of the paper are included in Section 5 and finally I conclude in Section 6.

2 A Collective Model of Household Behavior and Child Outcomes

In this section I describe the economic model used to rationalize investments in children together with household behavior. Each household (h) is composed of two agents (j), namely the father (f) and the mother (m). In each household, there is also one child[4] with a level of skills denoted by (s), who is not a decision maker.[5] In each period t, parents make decisions of time investments in their children (e_t^j) and monetary investments for the child (I_t), private consumption (c_t^j) and labor market (h_t^j) decisions. I assume that the decision of labor market participation is made only at the extensive margin, that is, members decide whether or not to participate in the labor market: $h_t^j \in \{0, 1\}$[6]. Additionally, during the first period, parents need to decide whether or not the child attends preschool (a_t) and then a_t can take the value of zero or one depending on whether the child goes or not to preschool. Finally, each individual has a preference shock associated to each combination of labor supply and childcare decision: ε_{t,d_t^j} where d_t^j indicates

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

[5]The assumption of having the child not as a decision maker is common in the literature (Del Boca et al., 2014; Bernal, 2008). That seems reasonable given the little influence that children under six years of age can have on the resource allocation of the household.

[6]This assumption is reasonable for the case of Chile since there is very low incidence of part-time work: the distribution of hours worked is unimodal for men and bimodal for women around zero and 45 hours a week. I provide evidence of this in the online appendix, in Section A and Figure A.1. Additionally, unemployment levels are very low compared to international standards, at about 5%.

the action taken by agent j according to the following mapping:

$$d_1^j = \begin{cases} 0 & \text{if } h_1^j = 0 \text{ and } a_1 = 0 \\ 1 & \text{if } h_1^j = 1 \text{ and } a_1 = 0 \\ 2 & \text{if } h_1^j = 0 \text{ and } a_1 = 1 \\ 3 & \text{if } h_1^j = 1 \text{ and } a_1 = 1 \end{cases} \tag{1}$$

and given that in the second period there is no decision regarding preschool/childcare attendance, $d_2^j = h_2^j$. This utility function incorporates the fact that it is costly to invest time in children, and it is costlier to parents who work. Additionally, the utility penalty of participating in the labor market is different depending on whether the parents send their child to preschool services or not. The flow utility derived for each parent j in the first period is given by the following utility function:

$$u_1^j(c_1^j, h_1^j, e_1^j, d_1^j, s_1) = \alpha_{1,1}^j \ln(c_1^j) + \alpha_{2,1}^j \ln(s_1) - \alpha_{3,1}^j (h_1^j) - \alpha_{4,1}^j e_1^j - \alpha_{5,1}^j e_1^j h_1^j - alpha_{6,1}^j h_1^j (1-a_1) + \sum_{m=0}^{3} q_{1,m} \varepsilon_{1,m} \tag{2}$$

where $q_{1,m}$ is an indicator function if decision m is taken. That is: $q_{1,m} := \mathbb{1}\{d_1^j = m\}$ where $\mathbb{1}\{\}$ is the indicator function taking the value of 1 if the statement inside $\{\}$ is true and zero otherwise. The coefficients of Equation 2 are normalized so that their sum is equal to one.

Given that parents don't make decisions about preschool/daycare during the second period, the flow utility for agents in that period is defined by:

$$u_2^j(c_2^j, h_2^j, e_2^j, d_2^j, s_2) = \alpha_{1,2}^j \ln(c_2^j) + \alpha_{2,2}^j \ln(s_2) - \alpha_{3,2}^j (h_2^j) - \alpha_{4,2}^j e_2^j - \alpha_{5,2} e_2^j h_2^j + \sum_{m=0}^{1} q_{2,m} \varepsilon_{2,m} \tag{3}$$

Additionally, I allow for a cost shifter in the time investments provided by parents given by $\alpha_{4,t}^j = \alpha_{4,0,t}^j + \alpha_{4,1,t}^j HM_t$. HM_t takes the value of one if, in addition to both parents, there is a person helping with household chores such as cleaning the house, cooking or taking care of the child. Otherwise, HM_t is equal to zero.

In period t, the skills of the child depend on monetary investments (I_t), time investments from both parents (e_t^j), preschool attendance (a_t), the skills of the child's primary caregiver (PG), which are constant over time[7], the previous level of skills (s_{t-1}) and the age of the child in months (τ_t). I allow for unobserved heterogeneity in the production of skills denoted by ($\eta_{s,t}$). The production of skills is specified in the following equation:

$$s_t = r_t s_{t-1}^{\theta_0} \tilde{I}_t^{\theta_1} e_t^{\theta_2} \tag{4}$$

where r_t is the total factor productivity given by:

$$r_t = \underbrace{\exp\left(\delta_0 + \delta_1 \tau_t + \delta_2 a_t + \delta_{3,t} PG + \delta_4 \text{Members}_t + \eta_{s_t}\right)}_{\text{Total Factor Productivity}} \tag{5}$$

The variable Members_t denotes the number of household members present in period t in the household. This captures the idea that, by having additional household members, not only might the production of skills be affected but also the productivity of each input. The distribution of the unobserved heterogeneity term is gender-specific. $\eta_{s,t} \sim f^g_{\eta_{s,t}}$ where $g \in \{boy, girl\}$. e_t is the total time effort invested in the child, given by the production function:

$$e_t = \underbrace{\left[\gamma_0 \left(\tilde{e}_t^f\right)^{\phi} + \gamma_1 \left(\tilde{e}_t^m\right)^{\phi}\right]^{1/\phi}}_{\text{Total effective time investment}} \tag{6}$$

where $\tilde{e}_t^j = e_t^j \exp\left(\eta_{e_t^j}\right)$ and $\tilde{I}_t = I_t \exp\left(\eta_{I_t}\right)$. The terms $\eta_{e_t^j}$ and η_{I_t} are unobserved heterogeneity. This term captures the fact that parents can differ in unobserved ways in how productive they are in terms of the time and monetary investments in their children. That is, even with the same amount of effort and monetary investment, the productivity of these inputs might be different across households.

[7] There is evidence pointing to the fact that cognitive skills remain stable at around age 8 and non-cognitive skills are stable during adult life (Borghans, Duckworth, Heckman, & Ter Weel, 2008; Roberts, Kuncel, Shiner, Caspi, & Goldberg, 2007). For this reason, assuming that skills of adult members are stable is reasonable.

2.1 Household's problem

I assume that parents need to make investment decisions for two periods. Each period lasts for two years and the first period starts when children are on average three years old. After the two periods, children enter a different stage in which parents and children face a different set of incentives in the process of skills production. Parents face a different set of incentives given that children start the formal schooling years and start behaving more as agents making their own decisions, which might have consequences for their own skills. For this reason, I only model childhood lasting for two periods: when children are three years old and when they are five years old[8]. The value of the household's problem at the beginning of the second period is given by:

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

$\mu \in [\underline{\mu}, \bar{\mu}] \subseteq [0,1]$ represents the Pareto weight or bargaining power of the father, which is normalized to be between zero and one. I impose a parametrization of the Pareto weight commonly used in the literature[9] given by:

$$\mu_t(E_t) = \frac{\exp(\Lambda' E_t + \nu_{\mu_t})}{1 + \exp(\Lambda' E_t + \nu_{\mu_t})} \tag{8}$$

where $\Lambda \in \mathbb{R}^L$ is a vector of coefficients; E_t are variables affecting the the relative bargaining power of each member in the household; and $\nu_{\mu,t}$ is unobserved heterogeneity. $\underline{\mu}$ and $\bar{\mu}$ are the lower and upper bounds for the Pareto weight.[10] In the E_t variables, I include the ratio of offered wages, the difference in ages between spouses, the difference in grades of schooling and the father's share in non-labor income. Additionally, I include conditions of the local labor market, which include the relationship between male and female unemployment, the sex ratio and the wage ratio in the region of residence of the household. Similar specifications to this one

[8]This assumption is commonly made in the literature. Bernal (2008) assumes that early childhood relevant decisions are made until age 5. Del Boca et al. (2014) model household behavior until children are 16 years old but only use information on two periods to estimate their model, that is, when children are on average four and nine years old.

[9]See, for instance (Cherchye et al., 2012), Bruins (2015) and Browning, Chiappori, and Lewbel (2013).

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

have been used previously in the literature.[11]

$$E_t = \left[\frac{w_t^f}{w_t^m}, \frac{Y_t^f}{Y_t^f + Y_t^m}, age_t^f - age_t^m, yrschool_t^f - yrschool_t^m, \frac{\bar{Female_t}}{\bar{Male_t}}, \frac{U^{Male_t}}{U^{Female_t}}, \frac{w^{Male_t}}{w^{Female_t}} \right] \tag{9}$$

where w_t^j denotes the wage offer for member j, Y_t^j denotes non-labor income in the hands of member j. Elements in Y_t^j include transfers from family members, cash transfers, and financial returns, among others. age_t^j is the age of each member and $yrschool_t^j$ is the maximum grade of schooling attained. $\frac{\bar{Female_t}}{\bar{Male_t}}$ is the sex ratio in the region of residence of the household, $\bar{U}$ denotes the unemployment rate for each gender, and $\frac{w^{Male_t}}{w^{Female_t}}$ is the wage ratio between women and men in the region of residence. These variables are what the literature refers to as distribution factors, variables that affect the behavior of the household only through its effect on the bargaining power.

The solution for the problem of the household should satisfy the technological constraint given in 4, the time constraint for each agent:

$$h_2^j \in \{0, 1\}, \text{ for } j = m, f, \tag{10}$$

the non-negativity constraint:

$$c_2^f, c_2^m, I_2, e_2^f, e_2^m \geq 0, \tag{11}$$

and the budget constraint

$$c_2^f + c_2^m + P_{I,2} I_2 + P_{a,2} = Y_2^f + Y_2^m + w_2^m h_2^f + w_2^f h_2^f + \Xi_2 \tag{12}$$

where w_2^j represents the wage offer for individual j, Y^j is the corresponding non-labor income, and Ξ_2 is the total non-labor income that cannot be attributed to any specific household member.[12] $P_{I,2}$ is the price of monetary investments in children for the second period. Note that in the second period parents don't make decisions regarding childcare attendance so they have to

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

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

pay price of preschool[13].

The state space Ψ_2 is given by:

$$\Psi_2 = \{r_2, s_1, \boldsymbol{\eta}_2, \Xi_2, \mu_2, \{Y_2^j, w_2^j, \boldsymbol{\epsilon}_{\mathbf{2}}^j\}_{j=m,f}, P_{I,2}\} \tag{13}$$

where the vector $\boldsymbol{\eta}_2$ collects the unobserved heterogeneity: $\boldsymbol{\eta}_t = \{\eta_{I_t}, \eta_{e_t^f}, \eta_{e_t^m}, \eta_{s_t}\}$ and $\boldsymbol{\epsilon}_{\mathbf{2}}^j$ is the two-dimensional vector of preference shocks for agent j.

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

$$V_1(\Psi_1) = \max_{\{I_1, a_1, \{c_1^j, e_1^j, h_1^j\}_{j=m,f}\}} \mu_1 u_1^f(c_1^f, h_1^f, e_1^f, d_1^f, s_1) + (1-\mu_1) u_1^m(c_1^m, h_1^m, e_1^m, d_1^m, s_1) +$$

$$\beta\, \mathbb{E}_{f_{\eta_2}}\left[V_2(\Psi_2) \mid \Psi_1\right] \tag{14}$$

subject to the skill production technology given in 4, the non-negativity constraint:

$$c_1^f, c_1^m, I_1, e_1^f, e_1^m \geq 0, \tag{15}$$

and the budget constraint:

$$c_1^f + c_1^m + P_{I,1} I_1 + P_a a = Y_1^f + Y_1^m + w_1^m h_1^f + w_1^f h_1^f + \Xi_1 \tag{16}$$

The expectation is taken with respect to the distribution of heterogeneity in the second period: $\boldsymbol{\eta}_2 = \{\eta_{I_2}, \eta_{e_2^f}, \eta_{e_2^m}, \eta_{s_2}\}$. The state space in the first period is given by:

$$\Psi_1 = \{r_1, s_0, \boldsymbol{\eta}_1, \Xi_1, \{\boldsymbol{\epsilon}_{\mathbf{1}}^j, Y_1^j, w_1^j\}_{j=m,f}, P_a, P_{I,1}, \mu_1, \mu_2\} \tag{17}$$

where $\boldsymbol{\epsilon}_{\mathbf{1}}^j$ is the four-dimensional preference shock for agent j and s_0 corresponds to skills in period zero, which is interpreted as health at birth. Note that both, μ_1 and μ_2 are included as part of the state space. Given that I do not include the problem of commitment in the relationship

[13] The price that families pay include not only tuition fees, which in most cases is zero, but also incorporates other costs such as transportation.

-the possibility of dissolving the union[14]- I allow agents to be able to have complete information regarding the bargaining power today and tomorrow[15].

I allow for cost-shifters for the price of childcare and of monetary investments in children. Specifically, the price of childcare depends on the distance to the nearest childcare provider. The price of monetary investments depends on the relative supply of childcare centers in the household's neighborhood. Neighborhoods with a relatively large supply of such centers could, in principle, offer relatively larger supply of other types of goods or services for children and thus, could shift the cost of such investments. The prices will then be given by the following specification:

$$P_a = \text{Pchildcare}_{a,0} + \text{Pchildcare}_{a,1} DChildcare \tag{18}$$

$$P_{I,t} = \text{Price}_{I,0} - \text{Price}_{I,1} Dens_t \tag{19}$$

where *DChildcare* is the distance to the nearest preschool provider, in meters, and $Dens_t$ is the number of preschool/daycare providers within 5km of the household[16].

2.2 Model solution

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

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

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

[14]The commitment problem is part of the main point of the paper. Such question has been explored previously in the literature. See for instance, (Tartari, 2015).

[15]Note that an equivalent formulation of the problem will be to have only one Pareto weight valid for the two periods but where it is discounted for the second period

[16]Section B of the Online appendix provides evidence suggesting that the these measures modify the price of childcare and investments in children.

$$c_2^{f,*} = \max\{\frac{\alpha_{1,2}^f \mu_2 I_2}{\theta_1 \kappa_2^2(\mu)}, \zeta\} \tag{22}$$

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

$$e_1^{m,*} = \frac{\left[\kappa_2^2(\mu_2)\theta_2 + \beta \kappa_2^2(\mu_2)\theta_2\theta_0\right]\gamma_1}{(1-\mu)\alpha_{4,2}^m(1+h_2^m)} \xi_1(m)\exp\left(-\eta_{e_1^m}\right) \tag{24}$$

$$e_1^{f,*} = \frac{\left[\kappa_1^2(\mu_1)\theta_2 + \beta \kappa_2^2(\mu_2)\theta_2\theta_0\right]\gamma_0}{\mu \alpha_{4,2}^f(1+h_2^f)} \xi_1(f)\exp\left(-\eta_{e_1^f}\right) \tag{25}$$

$$c_1^{f,*} = \max\{\frac{\alpha_{1,2}^f \mu_2 I_2}{\theta_1 \kappa_1^2(\mu_1) + \beta\theta_0\theta_1\kappa_2^2(\mu_2)}, \zeta\} \tag{26}$$

$$c_1^{m,*} = \max\{\frac{\alpha_{1,2}^f \mu_2 I_2}{\theta_1 \kappa_1^2(\mu_1) + \beta\theta_0\theta_1\kappa_2^2(\mu_2)}, \zeta\} \tag{27}$$

$$I_2^* = \frac{\kappa_2^2(\mu_2)\theta_1\left(h_2^f w_2^f + h_2^m w_2^m + Y_2^f + Y_2^m + \Xi\right)}{\kappa_2^1(\mu_2) + \kappa_2^2(\mu_2)\theta_1 P_I}\exp\left(-\eta_{I_2}\right) \tag{28}$$

$$I_1^* = \frac{\left[\kappa_1^2(\mu_1)\theta_1 + \kappa_2^2(\mu_2)\theta_0\theta_1\beta\right]\left(h_2^f w_2^f + h_2^m w_2^m + Y_2^f + Y_2^m + \Xi - P_a a\right)}{\kappa_1^1(\mu_1) + \kappa_1^2(\mu_1)\theta_1 + \beta\theta_0\theta_1\kappa_2^1(\mu_2)}\exp\left(-\eta_{I_1}\right) \tag{29}$$

where

$$\xi_t(j) = \frac{\left(\gamma_j \mu \alpha_{4,t}^f(1+h_t^f)\right)^{\frac{\phi}{1-\phi}}}{\gamma_0\left[\gamma_0(1-\mu)\alpha_{4,t}^m(1+h_t^m)\right]^{\frac{\phi}{1-\phi}} + \gamma_1\left[\gamma_1\mu\alpha_{4,t}^f(1+h_t^f)\right]^{\frac{\phi}{1-\phi}}} \tag{30}$$

$$\kappa_t^i(\mu) = \mu\alpha_{i,t}^f + (1-\mu)\alpha_{i,t}^m \tag{31}$$

$$\gamma_j = \begin{cases} \gamma_0 \text{ if } j = f \\ \gamma_1 \text{ if } j = m \end{cases} \tag{32}$$

$\zeta = 1.0e-5$ is a normalization set for the utility function when consumption is zero. The optimal decisions of labor supply and childcare are given by:

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

$$
(1-\mu_2) u_2^m \left(c_2^{m,*}(h_2^f, h_2^m), h_2^m(h_2^f, h_2^m), e_2^{m,*}(h_2^f, h_2^m), d_2^m(h_2^f, h_2^m), s_2(h_2^f, h_2^m) \right) \tag{33}
$$

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

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

$$
+ \beta \, \mathbb{E}\left[V_2(\Psi_2(h_1^f, h_1^m, a) \mid \Psi_1 \right] \tag{34}
$$

3 The Early Childhood Longitudinal Survey of Chile

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

The ECLS includes multiple test scores for children and questionnaires answered by the primary caregiver of the child in order to assess the skills level of children, for different domains such as socio-emotional development, behavioral problems and development of vocabulary. Not every test was answered by all the children, as all of them include different age specifications.[17] The description of the tests included in the sample is included in Tables 1 and 2. I use

[17]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

these test scores as noisy information about children's skills.

Descriptive statistics of the sample used are reported in Table 3. I restrict the sample to families who were surveyed in both waves and where both parents are living with the child. Additionally, since the model analyzes households with one child, I include only households where there is only one child or if there are siblings, they are more than five years apart[18]. The description of how the sample is restricted is included in Table 4.

We see that fathers, whose average age is 37.4, are on average three years older than mothers, whose average age is 34.5. There is not much difference in terms of schooling, as both fathers and mothers attain on average 11 grades of education. We do observe important differences between fathers and mothers in labor market outcomes. Fathers participate in the labor market, on average, 43 hours a week, whereas the corresponding figure for mothers is 24.22 hours. This large difference is not explained by unemployment but, rather, because women are out of the labor force and not looking for a job. Household chores, including caring for children, largely explains low levels of female labor force participation[19].

There are differences in the wages of men and women in the sample. The average weekly wage of a woman is \$82,730 Chilean Pesos (CLP) whereas men make \$85,480CLP.[20] In terms of ages of children, we see that in the second wave, in 2012, they are on average 64 months old.

The survey also reports the frequency with which parents perform different types of activities with their children. The description of each of these activities is presented in Tables 5 and 6. I do not present detailed descriptive statistics about time investments of parents in their children in the main body of the text but such description is included in Section D of the Online appendix. The data shows that mothers spend more time than fathers in every activity, even after controlling for labor force participation.

The dataset also includes information about other type of investments that parents make in their children such as availability of toys, music, and food, puzzles, books for children, among others. Previous studies such as Del Boca et al. (2014) and Bernal (2008) take into account such factors in the production of skills in children but do not observe such measures of investments.

skills in young children.

[18](Bernal, 2008) and Del Boca et al. (2014) impose similar restrictions.

[19]This point is further developed in Section C of the Online Appendix.

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

The identification of how monetary investments affect the production of skills in children in their studies relies, then, on functional forms assumptions. Going beyond previous studies, this information will shed some light on how parents invest in their children and what are the main tradeoffs faced by families when making such investments. Some of these measures are exactly the same as those used in Cunha et al. (2010), which come from the HOME inventory test score. The details of the measures used to asses the level of monetary investment in the children can be found in Tables 7 and 8 .

The dataset also includes information related to health at birth such as height and weight at birth, incidence of preeclampsia, depression or anxiety during pregnancy, and alcohol or drug abuse during pregnancy, among others. The information about health at birth is described in Table 9. The dataset also contains information about cognitive and non-cognitive skills for the child's primary caregiver. This information is described in Table 10.

One of the key features of the economic model is the Pareto weight, the relative importance, of each household member. The dataset contains information regarding female empowerment and gender roles that I use as noisy measures of the Pareto weight of each member. The measures used are described in Table 11.

In addition to the ECLS, I use information about the location of every preschool provider in Chile and I compute the distance from each center to each household[21]. I use the relative availability of preschool providers near each household as a shifter in the cost of childcare and monetary investments in children as indicated in Equation 18. Finally, I use information from the household survey (CASEN) in 2011, together with the CENSUS dataset in order to obtain some of the distribution factors introduced in Equation 9. The descriptive statistics of the distribution factors can be found in Table 12.

4 Estimation

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

[21] Section E of the Online Appendixprovides a detailed description of this dataset

the latent variables in the model:

$$K = \{\{\ln(s_t), \ln(e_t^{f,*}), \ln(e_t^{m,*}), \ln(I_t^*), \mu_t\}_{t=1,2}, \ln(PG), \ln(s_0)\} \tag{35}$$

I assume that the relationship between the measures and the latent factors $k \in K$ is given by the following linear system:

$$Z_m^k = \iota_{m,0}^k + \iota_{m,1}^k k + \varepsilon_m^k \text{ for } m = 1...N_k \tag{36}$$

where Z_m^k denotes the measure m for the latent variable $k \in K$ and N_k denotes the number of measures available for the latent factor k. The variables used as measures for each factor are described in Tables 1, 2 and Tables 5 to 11. ε_m^k is the corresponding measurement error in the measurement system. For instance, we do not observe directly skills for children during 2010. However, the test scores included in Table 1 are noisy measures related to the log of skills in 2010 ($\ln(s_1)$)via Equation 36. Given the structure of the model, there is a well-defined likelihood function denoted by:

$$f(O|X;\Theta) = \mathscr{L}(\Theta|O;X) \tag{37}$$

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

$$O_0 = \{\{Z_m^{\ln(PG)}\}_{m=1}^{N_{\ln(PG)}}, \{Z_m^{\ln(s_0)}\}_{m=1}^{N_{\ln(s_0)}}\}$$

That is, the observed outcomes in period 0 correspond exclusively to the measures used for health at birth s_0 and the measures used for skills of the primary caregiver PG. For t=1 the set of observed outcomes is given by:

$$O_1 = \{h_1^f, h_1^m, a_1, \mathscr{Z}_1\} \cup \underbrace{\{w_1^f\}}_{\text{if } h_1^f>0} \cup \underbrace{\{w_1^m\}}_{\text{if } h_1^m>0}$$

that is, the decision of labor supply for each member (h_1^f, h_1^m), wages (w_1^f, w_1^m) for those who participate in the labor market, preschool/daycare decisions a_1 and the set of observed measures $\mathscr{Z}_1$ which consists of all measures used for the latent factors in the first period:

$$\mathscr{Z}_1 = \{\{z_m^{\ln(s_1)}\}_{m=1}^{N_{\ln(s_1)}}, \{z_m^{\ln\left(e_1^{f,*}\right)}\}_{m=1}^{N_{\ln\left(e_1^{f,*}\right)}}, \{z_m^{\ln\left(e_1^{m,*}\right)}\}_{m=1}^{N_{\ln\left(e_1^{m,*}\right)}}, \{z_m^{\ln\left(I_1^*\right)}\}_{m=1}^{N_{\ln\left(I_1^*\right)}}\} \tag{38}$$

The set of observed outcomes for the second period does not include the childcare decisions but includes the measures used for the Pareto weight, which are described in Table 11 and are only included in the second period.

$$O_2 = \{h_2^f, h_2^m, \mathscr{Z}_2\} \cup \underbrace{\{w_2^f\}}_{\text{if } h_2^f>0} \cup \underbrace{\{w_2^m\}}_{\text{if } h_2^m>0}$$

$$\mathscr{Z}_2 = \{\{z_m^{\ln(s_2)}\}_{m=1}^{N_{\ln(s_2)}}, \{z_m^{\ln\left(e_2^{f,*}\right)}\}_{m=1}^{N_{\ln\left(e_2^{f,*}\right)}}, \{z_m^{\ln\left(e_2^{m,*}\right)}\}_{m=1}^{N_{\ln\left(e_2^{m,*}\right)}}, \{z_m^{\ln\left(I_2^*\right)}\}_{m=1}^{N_{\ln\left(I_2^*\right)}}, \{z_m^{\mu_2}\}_{m=1}^{N_{\mu_2}}\} \tag{39}$$

As the factors are not observed directly from the data, it is necessary to integrate over their distribution to obtain the likelihood function in terms of elements from the economic model:

$$\mathscr{L}(\Theta|O;X) = \int_{D_0} f_0(O_0, K_0|X;\Theta)dK_0 \times \int_{-\infty}^{\infty}\int_{D_1} f_1(O_1, K_1, K_0|O_0, X;\Theta)dK_1 d\ln(s_0) \times$$
$$\int_{-\infty}^{\infty}\int_{D_2} f_2(O_2, K_2, K_1|O_1, X;\Theta)dK_2 d\ln(s_1) \tag{40}$$

where f_t is used to denote a generic probability density function. The detailed derivation of the likelihood function is described in Section A.1 in the Appendix. The likelihood of period zero ends up being composed of two parts: the probability density function of the measurement system described in Equation 36 and the distribution of the factors in the first period. I assume that the error term in the measurement system follows a normal distribution centered around zero and that they are independent across measures:

$$\varepsilon_m^k \sim N(0, \sigma_{k_m}^2) \text{ for } m = 1 \ldots N_k, \forall k \in K \tag{41}$$

It is important to note, however, that the identification of the economic model does not rely on this particular functional form assumption, as will be discussed later. Similarly, I assume that the distribution of the factors is gaussian. However, I allow for correlation between the factors in period zero as it is reasonable to assume there is some degree of dependence between health at birth and skills of primary caregiver:

$$f(\ln(s_0)|\ln(PG)) = \mathcal{N}\left(\delta_{s_0}\ln(PG), \left(\sigma_{\ln(s_0)}\right)^2\right) \tag{42}$$

$$f(\ln(PG)) = \mathcal{N}(0, \ln(\left(\sigma_{\ln(PG)}\right)^2)) \tag{43}$$

For periods 1 and 2, in addition to integrating over the distribution of the factors of the corresponding periods, it is necessary to integrate over the distribution of the previous levels of skills since skills in period t depend on skills in period $t-1$. The likelihood in these periods also include the density of the measurement error for the measurement system. Additionally, we need to include the density of the factors. This is given by the density of the heterogeneity term η_t as well as the heterogeneity term in the Pareto weight v_t. For the factors $\left(e_t^{*,f}, e_t^{*,m}, I_t^{*,m}\right)$ I assume that the heterogeneity term follows a normal distribution centered around zero:

$$\eta_k \sim \mathcal{N}\left(0, \sigma_k^2\right), \text{ for } k = e_t^{*f}, e_t^{*,m}, I_t^{*,m} \tag{44}$$

And then, the pdf of these factors are obtained from the distribution specified in 44 together with the optimal levels of effort and investments found in 20, 21, 24, 25, 28 and 29. Now, the density of skills in period t is given by the distribution of the heterogeneity term η_{s_t} together with the production function specified in 4. I assume that the heterogeneity term follows a normal distribution and the mean of men is normalized to be zero to allow for gender-specific heterogeneity:

$$\eta_{s,t} \sim \mathcal{N}\left(\delta_s girl, \sigma_s^2\right) \tag{45}$$

where the variable *girl* takes the value of one if the child is a girl, zero otherwise. Finally, the density of the Pareto weight is given by the distribution of v_t combined with the parametrization specified in 8. I assume that skills of the mother shift the distribution of v_t and its distribution to be normal:

$$v_t \sim \mathcal{N}\left(\delta_\mu \ln(PG), \sigma_\mu^2\right) \tag{46}$$

The gaussian and independence assumptions made about the measurement system and the heterogeneity terms are not necessary for purposes of identification, as will be shown in Section 4.1. Such assumptions should be considered as simplifying rather than for identifying ones.

I assume a Mincer-type equation with Gaussian error term for the wages:

$$\ln(w_t^j) = \beta_0 + \beta_1 yrschool^j + \beta_2 age_t^j + \beta_3 \left(age_t^j\right)^2 + \varepsilon_{w_t^j} \tag{47}$$

$$\varepsilon_{w_t^j} \sim \mathcal{N}\left(0, \sigma^2_{w^j}\right) \tag{48}$$

Lastly, the preference shocks ε_t enter into the likelihood function. I assume a Gaussian distribution as well, centered around zero. Such preference shocks enter through their CDF as the probability of observing the actions of labor supply and childcare decisions, as being the optimal ones for each household.

The likelihood includes 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. However, skills in a given period depend on skills in previous period and this dynamic generate an additional difficulty: 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. Because of this curse of dimensionality, a pure simulation strategy would be computationally unfeasible.

I adapt a particle filter algorithm to estimate the model via simulated methods (Creal, 2012). The full description of the estimation technique and the derivation of the likelihood function are described in Appendix A.2. Other approaches such as the Kalman filter (Cunha & Heckman, 2008) or the unscented and extended Kalman filter have been proposed previously in the literature (Cunha et al., 2010). However, this would imply an approximation of the dynamics of the model that would possibly limit the non-linearities arising in the system (Fernández-Villaverde & Rubio-Ramírez, 2007). To the best of my knowledge, this is the first application of a particle filter algorithm in the estimation of a microeconomic model.

4.1 Identification

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

4.1.1 Measurement System

We can write the measurement system specified in Equation 36 in matrix form:

$$Z = \iota_0 + \iota_1 K + \varepsilon \tag{49}$$

where $Z \in \mathbb{R}^M$ contains all the measures available, M is the total number of measurements for all the factors, $K \in \mathbb{R}^{11}$ is the vector of 11 factors and $\varepsilon \in \mathbb{R}^M$ is measurement error. $\iota_1 \in \mathbb{R}^{M \times 11}$ is the matrix of factor loadings. As is common in factor analysis, a location and scale normalizations are necessary to ensure identification of the system. The first step is to normalize the first element of ι_1 for each measure to one, which corresponds to setting $\iota_{1,1}^k = 1$ for every factor $k \in K$ in Equation 36. The location normalization corresponds to setting the mean of each factor to a specified level. The arbitrary scale is set to be:

$$\mathbb{E}[\ln(s_0)] = \mathbb{E}[\ln(PG)] = 0$$
$$\mathbb{E}[\mu] = 0.5 \tag{50}$$

Note that, as found in (Agostinelli & Wiswall, 2016), skills only need to be normalized in period 0. I also set normalizations for effort levels and investments, which I will explain in full detail in Section 4.1.1. This normalization is irrelevant given that we can re-define new measures $Z - \iota_0$ and the analysis will remain unchanged. From the observed measures Z, I can obtain the covariances by noting that:

$$\Sigma_Z = \iota_1 \Sigma_K \iota_1' + \Sigma_\varepsilon \tag{51}$$

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

I still need to make further assumptions to recover all the relevant parameters. By making the assumption that the measurement error of the skills at birth is independent of the measurement error of the measures corresponding to the remaining factors, I have enough moments to identify all the parameters. Formally, the assumption is given by $\varepsilon_m^{\ln(s_0)} \perp\!\!\!\perp \varepsilon_{m'}^{k'}$ for $m = 1 \ldots N_{ln(s_0)}$, $k \neq \ln(s_0)$, $m' = 1 \ldots N_k$. This is a consequence of Theorem 1 in (Cunha et al., 2010).

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

$$\frac{Cov(Z_m^k, Z_1^{\ln(s_0)})}{Cov(Z_1^k, Z_1^{\ln(s_0)})} = \iota_{m,1}^k \tag{52}$$

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

$$\frac{Cov(Z_m^{\ln(s_0)}, Z_1^k)}{Cov(Z_1^{\ln(s_0)}, Z_1^k)} = \iota_{m,1}^{\ln(s_0)} \tag{53}$$

4.1.2 Distribution of latent factors

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

$$ME_j = \{\frac{Z_j^k}{\iota_{j,1}^k}\}_{k \in K} \tag{54}$$

$$me_i = \{\frac{\varepsilon_j^k}{\iota_{j,1}^k}\}_{k \in K} \tag{55}$$

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

$$\mathbb{E}[me_1 | K, me_2] = 0 \tag{56}$$

$$me_2 \perp\!\!\!\perp K \tag{57}$$

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

$$f(K) = \frac{\int_{-\infty}^{\infty} e^{-i\chi K} e^{\left(\int_0^{\chi} \frac{E\left[iME_1 e^{i\psi ME_2}\right]}{\left[e^{i\psi ME_2}\right]} d\psi\right)} d\chi}{2\pi} \tag{58}$$

The intuition behind the identification argument is that measures contain information about the true signal (the distribution of the factor) and the error. If we have at least two factors that satisfy some condition of independence, variation in these two factors that is common, is attributed to variation to the factor, as opposed to variation in the measurement error term. In terms of the elements of the likelihood function, this implies identification of the terms related to the Pareto weight, the effort levels, and the optimal level of investment.

Note, however, that in order to identify the density of skills, we need to take into account the heterogeneity term η_s. (Matzkin, 2007) shows a negative identification results in this case and illustrates that to be able to non-parametrically identify the function in which we are interested, we need to impose some restrictions. In particular, the assumption that the heterogeneity η_{s_t} term enters additively is enough to identify the technology of skills formation. This argument is also used in (Cunha et al., 2010). By identifying $f(K)$, we can obtain the density of skills in $t+1$ conditional on all other factors in period $t+1$ and on skills in period t.

$$f\left(\ln(s_{t+1})|\ln(s_t), e_{t+1}^{f,*}, e_{t+1}^{m,*}, I_{t+1}^{*}, \mu_t, \ln(PG)\right) \tag{59}$$

This is not exactly the technology of skills formation since we need to include the heterogeneity term. However, once we assume it enters additively, it is possible to recover the skill production function. Starting from the cumulative distribution function of s_{t+1} conditional on the aforementioned factors:

$$F_{\left(s_{t+1}|\ln(s_t), e_t^{f,*}, e_t^{m,*}, I_t^{m,*}\right)}\left(\bar{s}|\ln(s_t), e_t^{f,*}, e_t^{m,*}, I_t^{m,*}\right) = P\left(s_{t+1} \leq \bar{s}|\ln(s_t), e_t^{f,*}, e_t^{m,*}, I_t^{m,*}\right)$$

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

$$P\left(\eta_{s,t} \leq s_{t+1} - f_s\left(\ln(s_t), e_t^{f,*}, e_t^{m,*}, I_t^{*}\right)|\ln(s_t), e_t^{f,*}, e_t^{m,*}, I_t^{*}\right) \tag{60}$$

Then, we can recover the distribution of $\eta_{s,t}$ conditional on the other specified factors, which allows me to pin down the production function of skills as specified in 4

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

$$Cov(Z_m^l, Z_{m'}^{k'}) = \iota_{m,1}^{k}\iota_{m',1}^{k'}Cov(k,k') + Cov(\varepsilon_m^k, \varepsilon_{m'}^{k'}) \tag{61}$$

4.1.3 Preferences

The parameters of the economic model are identified by a combination of exclusion restrictions, exogenous sources of variations and functional form specifications. The main argument used to identify preferences of fathers and mothers follows standard procedures from the literature on collective models of household behavior (Chiappori & Donni, 2009). The use of distribution factors -variables that affect the behavior of the household but do not modify household behavior in any other way- allows me to identify preferences of mothers and fathers. The intuition of the identification argument is that variation in the distribution factors will change the behavior of the household through the bargaining power. This allows us to separately identify preferences of fathers and mothers. The distribution factors used in this article have been previously used in the literature (Cherchye et al., 2012; Attanasio & Lechene, 2014; Blundell et al., 2005).

First, I describe identification of the Pareto weight function specified in Equation 8 because, through this function, we can separately identify preferences of fathers and mothers. To identify parameters in Λ, I use exogenous variation in the gender wage gap, the unemployment gender gap and the sex ratio. The key assumption is that we have enough variation in the data for these factors, and variation is given in a way that is exogenous to the household. Finally, we need to have exogenous variation in the share of non-labor income earned by the man to secure identification of all the parameters in Equation 8.

The way in which the Chilean social security system schedules monetary transfers to households generates variation in the proportion of income earned by men in the household. The "Social Protection Card"[22] assigns a score to each household corresponding to its socioeconomic status. This score is used as the main targeting device through which monetary transfers are assigned to households, and all subsidies are given to mothers of children whenever there is a child in the household. The amount of the subsidy depends on an additional set of characteristics of the households, such as the number of children under 18 living in the household. There are seven different programs giving monetary transfers to families in Chile, but the basic ones correspond to the "Unique Family Subsidies" and "Family Assignments". Under these programs, a mother who earns less than \$187,515 CLP and has a score under 11.734 on the Social Protection

[22] "Ficha de Proteccion social" in Spanish

Card, is eligible to receive a transfer of $7,179 CLP per month, for each child under 18 and for herself. Additionally, families with a lower score on the Social Protection Card are eligible for subsidies, all received by the mother, depending on their score, the months they have currently been beneficiaries of the programs and the demographic composition of the household. The structure of the basic monetary transfers in Chile is reported in Figure 2. A description of how the monetary subsidies scheduling system has evolved over time is available in section F of the online appendix.

The discontinuities in the monetary transfer programs, as well as the variation in elements such as the number of members in the household, generates variation in the proportion of non-labor income in the hands of women. Finally, by assessing the extent to which responses in female empowerment and gender roles questionnaires changes are related to changes in the proportion of income earned by women and the distribution factors, we are able to identify the parameters in Equation 8.

To show identification of the remaining elements of the model, first I set the normalizations still needed for the remaining factors that were not normalized in Section 4.1.1. Effort (e_t^j) does not have natural units. I impose the following normalization:

$$\mathbb{E}\left[e_t^{f,*} \,|\, \mu = 0.5, h^f = 1\right] = 1 \tag{62}$$

Equation 62 normalizes the average effort of fathers, who have a Pareto weight equal to 0.5, and who participate in the labor market, to be one. This serves as location normalization. We also need to normalize the scale of this factor and to do so, I set $\alpha_{5,1}^j = 1$. This normalizes the scale of the factor as it states that the utility penalty for exerting a given level of effort is twice for parents who work than for those who don't work.

$$\mathbb{E}\left[I_t^* \,|\, \mu = 0.5, d = 10\right] = 1 \tag{63}$$

Similarly, in Equation 63 the average investments for families who have a Pareto weight of 0.5 and who have 10 childcare providers within 5 kilometers is normalized to one.

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

Identification of the remaining parameters follows standard arguments in the literature. For wages, as long as we have enough variation in education and age, we can identify the β coefficients. Similarly, the price elasticity of investments, with respect to the availability of preschool providers $P_{I,1}$, is identified as long as we have variation in the number of preschool providers within five kilometers of households. In Figure E.1, I show that there is significant variation in the data regarding this variable. The fact that Chile saw a massive expansion in the number of providers between 2006-2010 gives us significant variation in the data, as the system increased its capacity, measured in the number of children that the system can provide services for, by 450%. Following the normalization in Equation 63, and with the corresponding variation in childcare providers, we can identify the parameters $P_{I,1}, P_{I,0}$. Similar arguments are used to identify price of childcare [23].

5 Estimation Results

The results of the parameters estimated, together with the corresponding standard errors, are presented in Tables 13 - 21. We can see that childcare services liberate more time resources for mothers than for fathers. In the same regard, having one additional member in the household decreases the cost of time investments more for mothers than for fathers. We observe that mothers have stronger preferences for children than for consumption, when compared with fathers, and that fathers find it costlier to spend time with their child than mothers do. Having an additional person in the household helping with childcare or with household chores decreases the

[23] An additional test to asses if parameters are well identified in the model is to observe that the likelihood function is not flat on the parameter estimates. I have performed these tests to confirm that there is some curvature around the likelihood function. Although I do not report them due to the number of parameters included, the results are available upon request.

utility penalty of investing time in children, more for mothers than for fathers.

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

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

In Figures 1, and G.2 of the online appendix, I show the distribution of test scores according to the distribution of income in the sample. We do observe a significant gradient between socioeconomic status and cognitive achievement in five year old children. Additionally, we can combine test scores and estimates of the production function to obtain more precise estimates about the distribution of the skills in the estimation sample, the smoothing distribution. The smoothing distribution is an estimate of the probability density function of skills for each child using both, test scores and estimates of the production function, it is reported in Figure 3. We see that indeed wealth and skills are highly correlated even when children are five years old. Section H if the online appendix I include the description of how the smoothing distribution is constructed.

A by-product of the estimation results is the signal to noise ratio for each measure. That is, I am able to assess the proportion of the variance in a given measure that is due to measurement error or to true signal related to the underlying factor:

$$\text{Signal-noise ratio}_{m,k} = \frac{\iota_{m,1}^2 Var(k)}{\iota_{m,1}^2 Var(k) + Var(\varepsilon_m^k)} \tag{64}$$

The signal to noise ratio of each measure is presented in the online appendix in Section I. This is particularly useful for test scores as we are able to asses which tests measure more accurately skills for children. For instance, as shown in Table I.9, the Batelle-Cognitive test score is a less noisy measure of skills for children than the Tadi-Language test.

5.1 Model fit

The model does a good job when predicting labor force participation and childcare decisions of the household. Figure 4 reports the labor force participation of women in the 2010 and 2012 wave according to their education. In both waves, we see an increasing pattern in both, the data and the predicted pattern from the model. Figure 5 shows that the model also does a good job predicting male's labor force participation in both waves. The predicted and observed distribution of wages for both surveys is reported in Figure 6, where we observe that the model is able to replicate the main features of its distribution.

Regarding demand for preschool/daycare services, Table 22 shows that in the data, 67.7% of children whose mother works attend to childcare services whereas for non-working mothers is 42.9%. The corresponding figures for the predicted model are 68.4% and 42.9%[24].

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

From 2012 to 2016, the minimum amount of Cash Transfers given to families with children, in condition of disadvantage, has increased, in real terms, approximately by 72.8% from $14,340 CLP in 2010 to $28,327 CLP in 2016[25]. Although this represents a large increase, the current

[24] Given that some of the predicted values depend on unobserved shocks to the econometrician, the predicted version is done by setting the value of the shocks at its mean. In Section J of the Online Appendix I extend the results of the model fit showing the distribution of the fit given by the distribution of the corresponding shocks.

[25] 1$ USD $\approx$ 650 CLP. Inflation in Chile has been stable between 2% and 4% in that period. The details of how the cash transfer program operates and the description of how the amount of cash transfers have increased are

transfer is equivalent to 6% of the median income. Taking into account that in countries such as Brazil or Mexico the basic transfer can represent up to 25% of the median income, this is a small transfer compared to countries in the region (Fiszbein et al., 2009).

The first counterfactual exercise consists of analyzing such a policy of increasing the amount of cash transfers in the hand of households in the lowest quintile of the income distribution. By law, in households with children where both parents are present, such cash transfers are given to the mother. To asses the extent to which targeting cash transfers have different outcomes on child outcomes, in a second counterfactual exercise I simulate the effects of giving such cash transfers to fathers, rather than mothers. The third counterfactual scenario consists of using the same amount of resources for subsidies to childcare services. Finally, the fourth counterfactual scenario is given by using the same amount of resources to subsidize child investments. In the counterfactual scenarios, all policy beneficiaries consist of families in the lowest quintile of the income distribution.

5.2.1 Cash Transfers

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

The first counterfactual, giving the additional transfer to mothers, is implemented by setting the new budget constraints to the household setting non-labor income from the mother equal to the old non-labor income plus the additional transfer: $Y^m_{\text{new}} = Y_{\text{old}} + T$ where T corresponds to the transfer given, which corresponds to \$13,987 CLP. Note that cash transfers not only increase the budget constraint of the family but also shift the Pareto weight of each member as specified

included in Section F of the Online Appendix.

in Equation 8.

As a way to identify the extent to which targeting mothers as sole beneficiaries of cash transfers make a difference in the skill formation process of their children, the second counterfactual implemented consists of giving the same amount of money to fathers rather than mothers. Although the effect on the budget constraint is the same, such modification changes the Pareto weight towards the father.

5.2.2 Childcare Subsidies

Free childcare and preschool policies have also been very popular not only as a way to promote skills in young children but also as a tool to promote female employment. In 2013, the government of Chile established free and mandatory preschool services for children older than five years of age. Partly due to this policy, Chile is now the country with the highest expenditure on preschool education as a share of total government expenditure, among countries in the OECD. [26] Due to the increasing importance of such public policies, in the third counterfactual I simulate the effects of setting subsidies for preschool services for families located in the lowest quintile of the income distribution.

Childcare subsidies are implemented in the economic model by setting the price of the childcare services equal according to $P^f_{a,t} = P_{a,t} \times (1 - s_a)$ where s is the proportion of the price that is subsidized. In order to set the same costs as cash transfers, the total expenditure from the government by setting this subsidy should be equal to the total amount spent in the first and second counterfactual scenario. Given that all children go to such centers in the second period (2012) I simulate the effects only on the first period, 2010.

5.2.3 Subsidies to Monetary Investments

Finally, in the fourth counterfactual I simulate the effects of subsidizing monetary investments for children. Although probably less prevalent than childcare subsidies or cash transfers, programs aimed directly at increasing non-time investments in children from parents have been starting to be implemented in developing and developed countries. In Chile, for example, such

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

transfers are being done through the "Chile Crece Contigo"[27] (ChCC) program, established in 2009. ChCC is composed of a set of services for poor families with children younger than five years of age. The goal of the program is to guarantee that every child has the necessary resources so that they can achieve their full developmental potential during childhood. The program offers resources to parents such as a 24-hour phone line for inquiries about child development, and the distribution of books, toys, songs and story books for children, as well as providing learning materials to parents in order to increase their knowledge about child development. ChCC is the most important child development public program currently operating in Chile.

The program of subsidies to monetary investments for families is implemented in the economic model by setting the new price of investments according to: $P^f_{t,I} = P_{I,t} \times (1 - s_I)$. As in the case of childcare subsidies, in order to set the same cost for this policy intervention, the amount spent by the government subsidizing monetary investments should be equal to the case of the three aforementioned counterfactual scenarios. Finally, note that I could alternatively implement a policy of in-kind transfers to families where families would receive directly goods for child investments. However, such policy would potentially have higher implementation costs, as opposed to one subsidizing price of child investments. Moreover, to perform policy counterfactuals regarding such a policy it would be necessary to make some assumptions about the monetary costs of implementing such a policy. It is not clear at first hand how to make such assumption.

5.2.4 Results of Policy Interventions

The effects of the policy counterfactuals on employment are reported in Table 23. Cash transfers have a very limited effect on employment, a result that is consistent with the literature (Fiszbein et al., 2009). Childcare subsidies increase labor force participation but mostly for women. Such effect is consistent with the fact the high male labor force participation and low female labor force participation, together with the fact that women argue that the main reason they are not working is because of child care chores. The four policies have very limited effect on male employment.

[27] Chile Grows with You, in Spanish

The effects of policy counterfactuals on children's skills is reported in Table 24. We observe that both, maternal and paternal time investments increase in response to cash transfers. As labor force participation decreases, and it is less costly to exert time effort in children for non-working parents, it is not a surprise that we observe such effect. Additionally, paternal effort increases in a higher magnitude in response to cash to women than to cash of men. This is given by the fact that cash transfers empower women and thus their preferences are weighted more. As parental effort is a privately exerted effort with public benefits, it comes as no surprise that paternal effort increases more when women are relatively more empowered, that is, when they are the beneficiaries of cash transfers.

Out of the additional weekly \$3,252 CLP that families receive, only \$139 are spent in child investments and it does not make much of a difference if it is the mother or the father the recipient. The total effect of cash transfers is very limited, as we only see an increase of 0.4% of a standard deviation on the skills of children in disadvantage. This is consistent with the literature suggesting that cash transfers have limited effects on skills of children (J. Heckman & Mosso, 2014; Del Boca, Flinn, & Wiswall, 2016). Cases where cash transfers have been found to have a positive and significant effect on children's skills are often because of improvement in nutritional outcomes such as a decrease in the incidence of wasting and-or stunting (Paxson & Schady, 2010; Macours, Schady, & Vakis, 2012). Such a mechanism is unlikely to operate in Chile, where the incidence of stunting and wasting in children is below 1%.

As cash transfers have a negative effect on female labor force participation, this in turns increases the amount of time that mothers spend with their children. Due the complementarity of time investments, the productivity of paternal time investments increases and thus we observe an increase in both, paternal and maternal time investments as a consequence of cash transfers. The additional expenditure on child investments, as well as the increase in time investments from both parents, is what ultimately drives the increase in 0.4% of a standard deviation in skills for children.

Childcare subsidies have a total effect of increasing 0.05% of a standard deviation skills of children in beneficiary households. Childcare attendance by itself has a very limited effect when it comes to increasing skills of children, as can be seen from the point estimate of δ_2 in Table

18. However, childcare subsidies also affect the incentives faced by parents when it comes to monetary and time investments. The total change in employment depends on two effects. On the one hand, childcare subsidies make labor force participation less costly. On the other hand, they relax the budget constraint, further decreasing incentives for parents to participate in the labor market. As can be seen in Table 23, the effect on maternal employment is positive whereas that on paternal employment is slightly negative. This further translates in time investments that parents make in their children. Ultimately, childcare subsidies increase skills of children of beneficiary households in less than 1% of a standard deviation.

In Latin America, there is mixed evidence on childcare attendance and general child outcomes. Bernal et al. (2009) finds a negative effect of attendance to informal childcare services on health outcomes, but positive effects on learning outcomes for children whose exposure is more than 15 months, in Colombia. Rosero Moncayo et al. (2011) find that a negative effect of childcare on cognitive and language development in Ecuador. In Bolivia, (Behrman et al., 2004) find a positive effect of childcare attendance on children outcomes for those who attend more than seven months. It comes thus, as no surprise, that childcare attendance by itself has limited effects child's skills.

Using the same amount of money, \$3,252 CLP a week, to subsidize child investments, is the most effective policy to improve skills of children in disadvantage. We observe that the average treatment effect of such a policy is an increase in 3% of a standard deviation on skills. Note that this effect is exclusively driven by the increase in investments for children as the policy does not affect labor force participation.

In order to explore how general is the fact that subsidies to child investments are more productive than the other three alternatives, I simulate the effects of these policies for multiple levels of expenditure. Figure 7 reports the results of these policy counterfactuals, for different levels of expenditure, on children's skills. Childcare subsidies can only be implemented up to the point where all children attend childcare services. Beyond that point, price of childcare becomes negative and such a policy becomes similar to cash transfers. Regarding cash transfers, we observe that having the mothers as beneficiaries is slightly better than giving them to fathers, when it comes to children's skills. As can be seen, for every given level of expenditure, subsidies to child investments are more productive than the other three alternatives.

6 Conclusions

Skills developed during childhood affect adult life outcomes. This fact has motivated governments to implement policies aimed at increasing skills for children in disadvantage. However, there is still uncertainty about what are the most effective ways to increase skills in young children. This article contributes to the literature by comparing three policies and their effectiveness when it comes to promote skills for children in disadvantage.

To accomplish such a goal, I develop and estimate a technology of skill formation nested within a collective model of household behavior. The model allows parents to have different preferences in order to assess the extent to which targeting individual members have consequences in the process of child skill formation. By using a rich dataset on early childhood development, I am able to estimate the skill production technology via a dynamic-latent-factor structure a-là Cunha et al. (2010), which allows me to non-parametrically identify the fundamental parameters of the production function. The non-linearities in the skill production function imposes a challenge in the estimation strategy since traditional methods for factor models, such as the Kalman filter, fail in such a setting. In this paper, I implement a particle filtering technique in order to allow for the non-linearities in the skills production.

The results of this paper show that cash transfers have a very limited effect on reducing the gaps in skills between rich and poor children. Moreover, giving the transfers to fathers or mothers does not seem to make a significant difference. Consistent with most of the literature, I find that cash transfers have a very limited effect on female labor force participation. Childcare services have a positive but modest effect on skill promotion in children, as well as on female labor force participation. The main result suggests that the most effective way to close the gaps in skills between rich and poor children is by giving in-kind transfers. These are transfers that are given to households through a basket of goods that can be used to increase skills in their children, such as books, toys, puzzles and music.

7 Figures and Tables

Table 1: 2010 Tests-Measures of child skills

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

Table 2: 2012 Tests-Measures of child skills

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

Table 3: Descriptive statistics - Using 2012 wave of survey

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

Table 4: Description of sample used in the analysis

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

Table 5: Measures used for parental effort in 2012

Reads Children's storybooks or drawing books
Tells her stories
Sings to child
Takes her to parks
Takes her to cultural activities
Spends time with her chatting or drawing
Invites her to participate in household chores
Takes her to the supermarket
Shares a meal with her
Teaches the animals and their sounds
Teaches her the colors
Goes with her to visit friends or family members
Teaches her the numbers and how to count
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 6: Measures used for parental effort in 2010

Reads Childre's storybooks or drawing books
Tells her stories
Sings to her
Takes her to parks
Takes her to cultural activities
Plays with her
Spends time with her talking or drawing

*: 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 7: Measures used for Investment in 2012

Consumption of hamburger-pizza-fries*
Consumption of Fish-Beef-Chicken*
Consumption of bread-rice-pasta
Consumption of legumes*
Consumption of Chocolate-Candy*
Consumption of juice*
Consumption of snacks in bags*
Consumption of milk*
Consumption of water*
Consumption of cookies*
Consumption of fruits and vegetables*
Two or more toys to learn colors, sizes and shapes
Child has three or more puzzles
Music device where child can listen to music
Two or more toys for free expression (tools, costumes)
Two or more toys in to learn numbers
At least ten children's books available in the house
At least ten books for adults
Very little evidence of child living in household
Number of people with whom child shares bed
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 8: Measures used for Investment in 2010

Child has a special place to store toys
Child has at least one toy that involves muscular activity
Child has toys to pull and push
Child has at least one toy with wheels
Availability of plush toys-stuffed animals
Availability of mobiles for child
Availability of musical or literary toys
Child has three or more books of his own

*: 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 9: Measures used for health at birth

Mother diagnosed with Preeclampsia during pregnancy
Mother diagnosed with Cholestasis during pregnancy
Mother diagnosed with Urinary infections during pregnancy
Mother diagnosed with Hemorrages during pregnancy
Mother diagnosed with Hipertension during pregnancy
Mother diagnosed with Placenta Previa during pregnancy
Mother diagnosed with Diabetes G during pregnancy
Mother diagnosed with Anemia during pregnancy
Mother diagnosed with Toxoplasmosis during pregnancy
Mother diagnosed with Depression during pregnancy
Mother diagnosed with Bipolar D. during pregnancy
Mother diagnosed with Anxiety D. during pregnancy
Mother diagnosed with Obsesive compulsive D. during pregnancy
Mother diagnosed with Fobia during pregnancy
Mother diagnosed with Panic D. during pregnancy
Mother diagnosed with PTSD during pregnancy
Cigarrettes consumed during pregnancy
Cigarrettes consumed during the first six months of life of child
Alcohol consumption during pregnancy*
Substance abuse during pregnancy*
Child was born pre-term
Weight at birth (grams)
Height at birth (cm)

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

Table 10: Measures used for Skills of primary caregiver

Child has a special place to store toys
Child has at least one toy that involves muscular activity
Child has toys to pull and push
Child has at least one toy with wheels
Availability of plush toys-stuffed animals
Availability of mobiles for child
Availability of musical or literary toys
Child has three or more books of his own

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

Table 11: Measures used for Pareto weight

A woman who is in charge of most part of tasks of the household has no time to work*
Both spouses should contribute to household income*
Men should go to work and women should stay home*
Men should participate in household chores more actively than they actually do*
If my spouse earned enough there is no reason for me to work*
After having children, the best for a woman is to develop her carreer*
Having a payed job is very important in life*
Having a payed job is the best way for a woman to become independent*
Fathers time is as important as mothers time for child development*
It is better to have a bad marriage than to remain single*
Mother decides how to spend income
Father decides how to spend income
Both, father and mother, decide how to spend income
Mothers should take care of children
Fathers should take care of chidlren
Women's only activity should be taking care of children
Women should take care of chidlren and work part time
Women should work full time and delegate childcare to a third party
Men are the best suited to take care of children

*: 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: 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)	1.02	(0.06)
Unemployment ratio in region (Men/Women)	0.67	(0.11)
Wage ratio in region (Men/Women)	1.41	(0.07)

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

Table 13: Estimates: Utility function. Mother's preferences

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

Table 14: Estimates: Utility function. Father's preferences

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

Table 15: Estimates: Preference shock

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

Preference shocks for work-no childcare are standardized to zero

Table 16: Estimates: Mothers wages

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

Table 17: Estimates: Fathers wages

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

Table 18: Estimates: Production of Skills

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

Table 19: Estimates: Distribution of latent factors

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

Table 20: Estimates: Prices

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

Table 21: Estimates: Pareto weight

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

Table 22: Model Fit - Demand for childcare

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

Table 23: Effects of Policy Counterfactuals on Employment

	Change in Female labor force participation (%)	Change in Male labor force participation (%)
Cash transfer to mother	-2.37	-1.05
Cash transfer to father	-2.37	-1.05
Childcare subsidy	3.16	-2.11
Child-investments subsidy	0.00	0.00

Effects on policy beneficiaries. The reported effect is the average between the first and the second period.

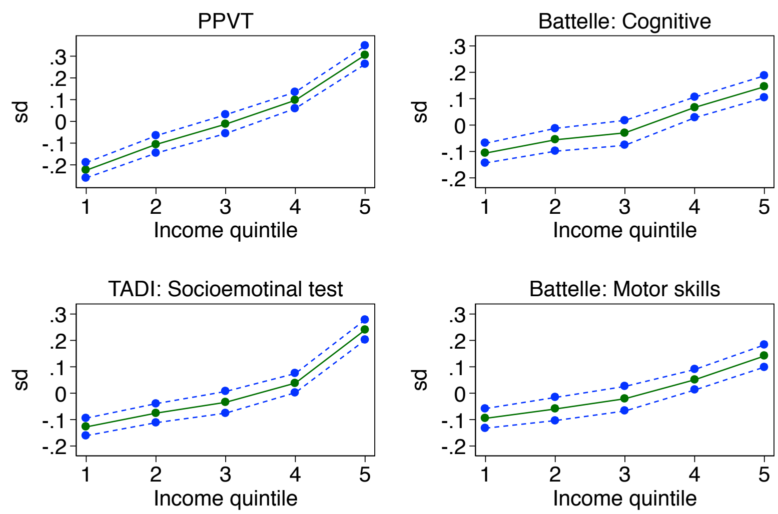
Table 24: Effects of Policy Counterfactuals on Children's Skills

	Maternal effort*	Paternal effort*	Child investments (CLP)*	Skills of children+
Cash transfer to mother	4.71	7.07	139.41	0.40
Cash transfer to father	4.71	2.08	139.21	0.40
Childcare subsidy	-1.05	8.68	155.71	0.05
Child-investments subsidy	0.00	0.00	3252.93	3.00

Effects on policy beneficiaries. The effect corresponds to difference between policy change and baseline situation. For maternal and paternal effort, as well as skills, The effects are given in standard deviations with respect to baseline. Child investments are given in CLP. ,

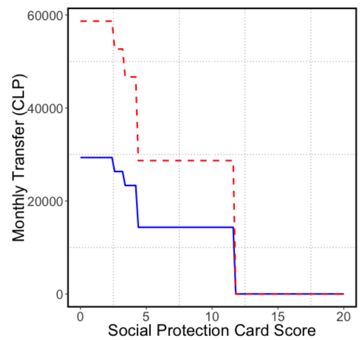
* Average effect between 2010 and 2012. For childcare subsidies, effect considered is in 2010.+ Total effect in 2012

Figure 1: Gaps in skills at age 5



The green (solid) line is the mean score, the blue (dashed) line is the 95% confidence interval. All test scores and parental assessments are normalized to have mean zero and variance one. PPVT stands for Peabody Picture Vocabulary Tests. Battelle is an instrument containing different scales to measures development of children. TADI is a test of learning and child development -"Test de Aprendizaje y Dessarollo Infantil" in Spanish-. In all tests, differences between the scores of children in the lowest quintile of the income distribution is statistically different to those children who are in the highest quintile of the income distribution.

Figure 2: Monetary Transfers to Families in Chile



This figure shows how monetary transfers to families are scheduled to families according to their score in the Social Protection Card. The total value of the transfer for each family corresponds to three different programs: "Unique Family Subsidies", "Family Assignments and "Social Protection Transfer". The conditions to be eligible for these programs are to have a score in the Social Protection Card below 11.734 and for those who work, having a monthly income of less than \$187,515 CLP. The final amount being transferred to the household also depends on the size of the household and the time they have been beneficiaries of such programs. The solid line represents the schedule for a bi-parental household with one child that has been in the program for 50 months. The dashed line corresponds to a bi-parental household with three children under 18 that has been in the program for less than six months.

Figure 3: Distribution of skills by Income
Smoothing distribution

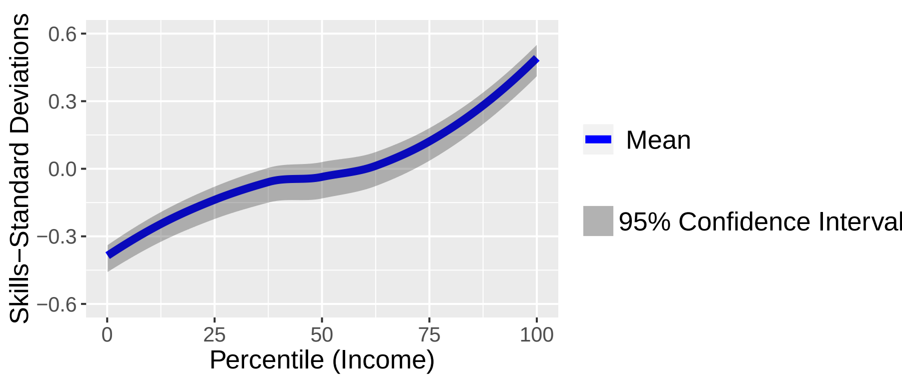
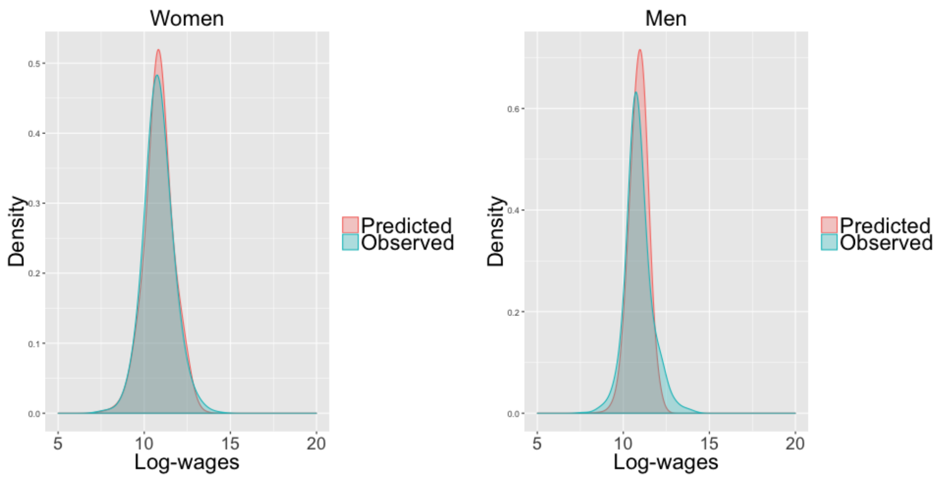


Figure 4: Model fit: Female labor force participation according to education

Figure 5: Model fit: Male labor force participation according to education

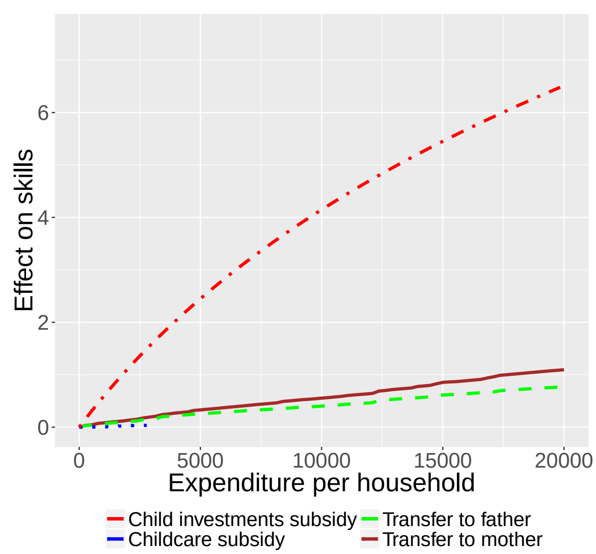
Figure 6: Model fit: distribution of wages



Kernel density estimates of predicted and observed wages.

Bandwidth chosen is 3.

Figure 7: Policy Effects on Children's Skills



The figure shows the effect of various policy counterfactuals on the skills of children located in the lowest quintile of the income distribution. The effect is measured as the number of standard deviations from the mean that the average level of skills for children in the lowest quintile of the income distribution is shifted.

A Appendix

A.1 Derivation of likelihood function

In this section I describe in detail how the likelihood function is constructed. The expressions will be left in terms of elements defined in Section 4.

$$\int_{D_0} f_0\left(O_0, K_0|X;\Theta\right)dK_0 = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f\left(\{\{Z_m^{\ln(PG)}\}_{m=1}^{N_{\ln(PG)}}, \{Z_m^{\ln(s_0)}\}_{m=1}^{N_{s_0}}\}|\ln\left(s_0\right), \ln\left(PG\right)\right) \times f\left(\ln(s_0), \ln(PG)\right)$$

$$= \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} \prod_{k\in\{\ln(s_0),\ln(PG)\}}\prod_{m=1}^{N_k} f_{\varepsilon_m^k}\left(Z_m^k - \iota_{m,0}^k - \iota_{m,1}^k k\right) f\left(\ln(s_0)|\ln(PG)\right) f\left(\ln(PG)\right) d\ln(s_0) d\ln(PG) \tag{65}$$

For the second period, the likelihood is:

$$\int_0^{\infty}\int_{D_2} f_2(O_2, K_2, K_1|O_1, X;\Theta) dK_2 d\ln(s_1) =$$

$$\int\ldots\int \underbrace{\prod_{k\in K_2}\prod_{m=1}^{N_k} f_{\varepsilon_m^k}\left(Z_m^k - \iota_{m,0}^k - \iota_{m,1}^k k\right)}_{\text{Measurement system}} \times \underbrace{\prod_{j=m,f} f(\varepsilon_{w_2^j})^{\mathbb{1}\{h_j==1\}}}_{\text{wages}} \times \underbrace{f_{(\nu_2|\mu_2)}\left(\nu_t|\mu_2\right)}_{\text{Pareto weight}} \times$$

$$\underbrace{f_{(\eta_{s_2}|K_2,\ln(s_1))}}_{\text{Skills of child}} \times \underbrace{\prod_{k\in\{\ln\left(e_2^{f,*}\right),\ln\left(e_2^{m,*}\right),\ln\left(I_2^*\right)\}} f_{\eta_k}\left(\eta_k\right)}_{\text{density of first set of factors}} \times \underbrace{P_\epsilon\left(d_2^{m,*}, d_2^{*,f}\right)}_{\text{Preference shock}} dK_2 d\ln(s_1) \tag{66}$$

where the term $P_\epsilon\left(d_2^{m,*}, d_2^{f,*}\right)$ is the cdf of the preference shocks for the observed decisions taken by the household $\left(d_2^{m,*}, d_2^{f,*}\right)$ given by the cdf of a normal distribution. Note that we also integrate with respect to skills in the first period $\ln\left(s_1\right)$ since skills in the second period depend on skills in the first period.

A.2 Particle filter algorithm

Filtering Algorithm

1. Set t=0.

   (a) For rr=1....RR:

      i. draw $(\ln(s_0), \ln(PG))^{\{rr\}}$ from proposal distribution $g((\ln(s_0), \ln(PG)|\Theta, X)$

      ii. Compute the weights $\hat{w}_0^{\{rr\}} = \frac{1}{RR}$

   (b) Compute likelihood for measurement system in $t = 0$: $\frac{1}{RR}\sum_{rr=1}^{RR} f\left(\{\{Z_m^{PG}\}_{m=1}^{N_{PG}}, \{Z_m^{s_0}\}_{m=1}^{N_{s_0}}\}|\left(\ln(s_0), \ln(PG)\right)^{\{rr\}}\right)$

2. Set t=t+1

   (a) For rr=1....RR:

      i. Draw $K_t^{\{rr\}}$ from proposal distribution (transition equation): $p(K_t^{\{rr\}}|K_{t-1}^{\{rr\}}, \Theta, X)$

      ii. For each factor, compute the corresponding weights given by the measurement system $\tilde{w}_t^{\{rr\}} = \prod_{m=1}^{N_k} f_{\varepsilon_m^k}\left(Z_m^k - \iota_{m,0}^k - \iota_{m,1}^k k\right)$

      iii. Define $w_t^{\{rr\}} = \hat{w}_{t-1}^{\{rr\}}\tilde{w}_t^{\{rr\}}$

   (b) For rr=1...RR

      i. Define $\hat{w}_t^{\{rr\}} = \frac{w_t^{\{rr\}}}{\sum_{rr=1}^{RR} w_t^{rr}}$

   (c) Compute the likelihood for period t: $\sum_{rr=1}^{RR} \tilde{w}_t^{rr}\hat{w}_{t-1}^{rr}$

   (d) For rr=1....RR

      i. Re-sample RR particles $K_t^{\{rr\}}$ from step $(2.i)$ with probabilities $\hat{w}_t^{\{rr\}}$

      ii. Set $w_t^{rr} = \frac{1}{RR}$

In this application, I use as proposal $g((\ln(s_0), \ln(PG)|\Theta, X)$ the distribution characterized by the joint density of factors for period zero, specified in Equations 42 and 43. The transition density from which factors in $t = 1, 2$ are drawn is characterized by the distribution of heterogeneity, characterized in equation 44, and and the characterization of the factors given by the optimal solution of effort and investment in equations 20, 21, 24, 25, 28 and 29, the skill production specified in 4 and the Pareto weight specification in 8 .

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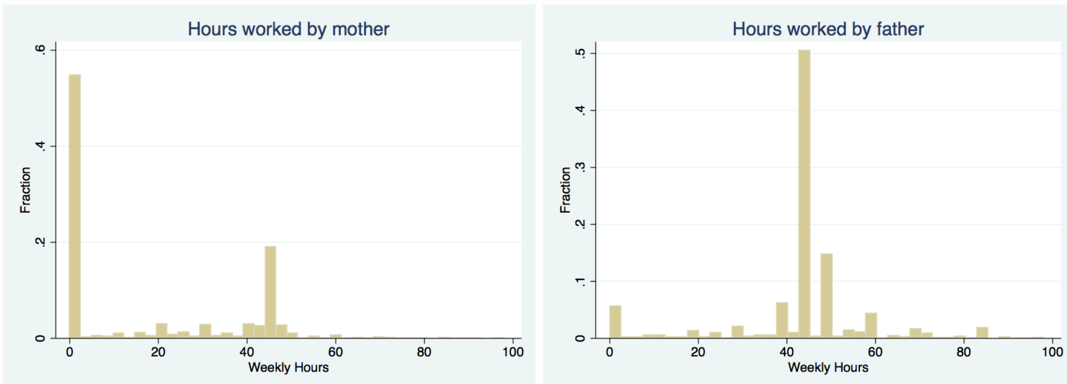
Online Appendix (Not for Publication)

A Labor force participation

Figure A.1: Distribution of work hours in Chile



I report the distribution of hours worked in Figure A.1. As can be seen, there is very little incidence of part-time work, most people work 45 hours a week or do not work at all. The information is taken from the ECLS. Similar results are found using the information from the national household survey of Chile, CASEN.

B Preschool Availability as Cost Shifter of Child Investments

In this section I provide evidence suggesting that the distance to the nearest childcare provider ($DChihldcare$) and the number of childcare providers within 5km of the household ($Dens$) can be used as shifters in the cost of childcare and monetary investments for children, respectively. I estimates the coefficients of the following equation:

$$y_i = \beta_0 + \beta_1 DChildcare_i + \beta_2 Dens_i + \beta_3 X_i + \varepsilon_i \tag{67}$$

where y_i is a given outcome and X_i is a vector including additional controls. As can be seen in the results of the estimates, in Table B.1, distance to the nearest childcare center is negatively related with preschool attendance and availability of music for children. The number of childcare providers in the neighborhood is positively related with availability of music for children, toys, and vegetable consumption. Additionally, I use different measures of availability of childcare centers to the household, including centers within 1, 2, and 10km. These results are reported in Table B.2. We see that all coefficients are significant except for availability of childcare centers at 1km.

Table B.1: Cost Shifters

VARIABLES	(1) Attends preschool	(2) Music for children	(3) Toys FE	(4) Vegetable Consumption
Childcare providers	0.00	0.01**	0.01**	0.03***
	(0.01)	(0.00)	(0.01)	(0.01)
Distance to childcare	-0.01**	-0.02***	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Observations	4,827	4,827	4,827	4,827
Adjusted R-squared	0.25	0.15	0.29	0.12

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

ToysFE: Toys for free expression

Childcare providers: Number of childcare providers within 5km to the household (hundreds)

Vegetable consumption: weekly frequency. Standardized (mean 0, sd 1)

Distance to childcare: Distance to nearest childcare-preschool service provider (km)

Additional controls: grades of schooling of both parents, WAIS verbal and numerical test scores for the mother, big-five personality traits test score for the mother, age of child, number of members living in the household, age of both parents, total income, activities that parents perform with their children and other investments done by parents

Table B.2: Distance: Robustness

VARIABLES	(1) Toys FE	(2) Toys FE	(3) Toys FE	(4) Toys FE
Within 1km	1.09			
	(0.87)			
Within 2km		0.55**		
		(0.28)		
Within 5km			0.12**	
			(0.05)	
Within 10km				0.03**
				(0.01)
Observations	4,827	4,827	4,827	4,827
Adjusted R-squared	0.29	0.29	0.29	0.29

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

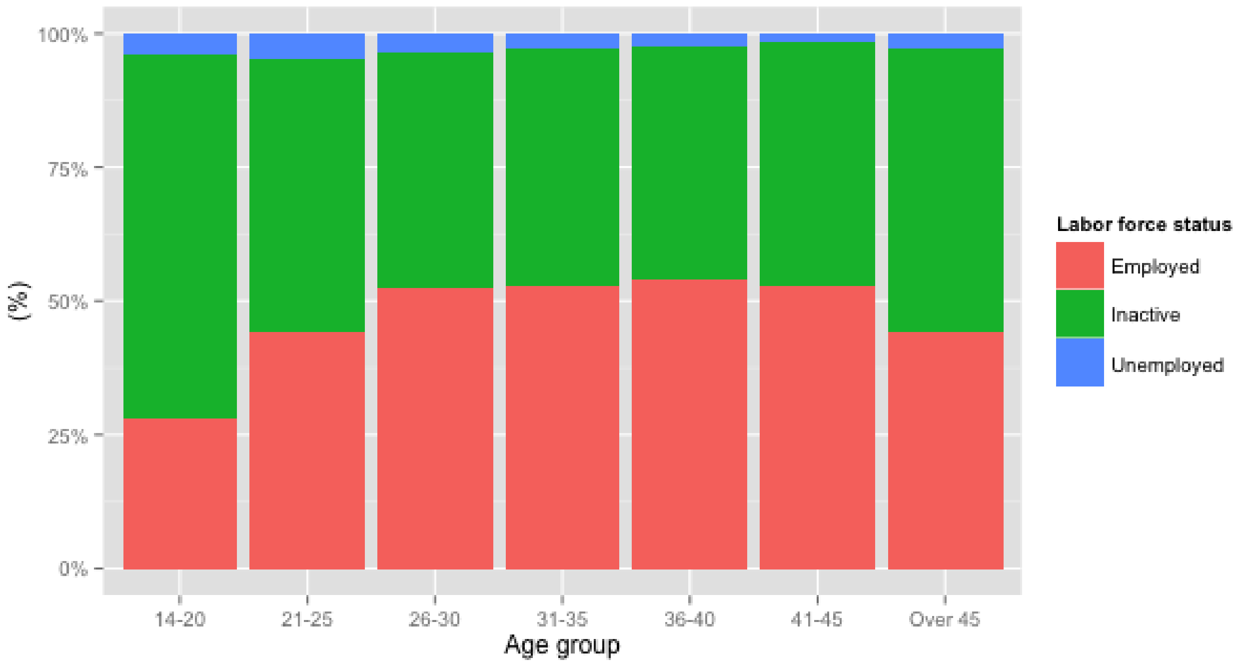
Additional controls: grades of schooling of both parents, WAIS verbal and numerical test scores for the mother, big-five personality traits test score for the mother, age of child, number of members living in the household, age of both parents, total income, activities that parents perform with their children and other investments done by parents

C Female Labor Force Participation

As mentioned before, mothers participate in the labor market , on average, for18 hours a week. The corresponding figure for fathers is 44 hours. One plausible explanation can be due to involuntary unemployment: it is harder for women to find a job offering a wage higher than their reservation wage, and because of that they do not actively participate in the labor market. However, it turns out to be the case that female unemployment in the population analyzed is low, below 5%. The main reason for observing these low levels of female participation in the labor market is due to voluntary unemployment: women with young children decide not to participate in the labor market. As can be seen in Figure C.1, this is characteristic of women across all age groups. Most of them are not working or looking for a job and 83% of them state that the main reason is that they do not do it is because they are taking care of children.

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

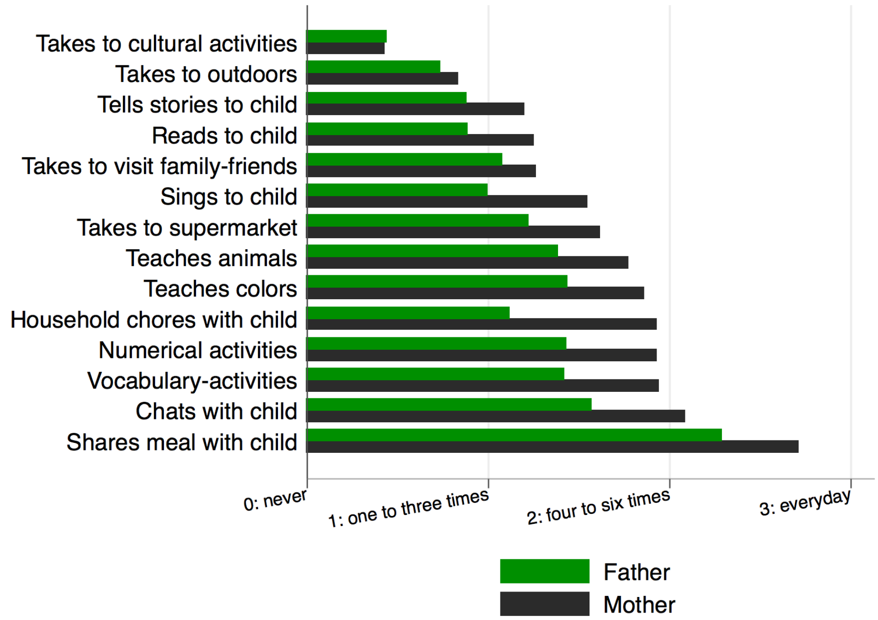
Figure C.1: Female Labor Force Participation (%)



D Parental Activities with Children

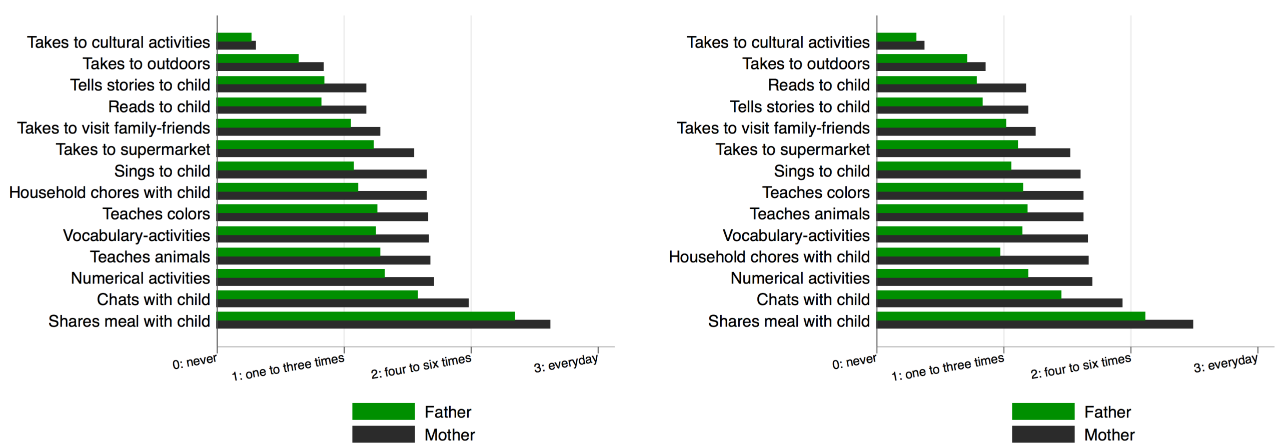
As shown in Figure D.1, mothers spend more time with their children, in every activity, than fathers do. This happens even when taking into account differences in labor supplies, as seen in Figures D.2. In Tables D.1 and D.2, I analyze the relationship between labor supply of both spouses and time spent with the child. In order to simplify the analysis, I construct a measure of time investment via principal component analysis and I regress the predicted factor with other covariates of the family. We observe that there is a negative correlation between time spent with the child and labor supply decisions for both fathers and mothers, in the two waves of the dataset being used, as can be seen in Tables D.1 and D.2.

Figure D.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 D.2: Frequency of activities by parental labor supply



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.

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

The evidence from these regressions is complemented with the estimates of regressions in differences reported in Table D.3. The results again seem to suggest that, as members participate more in the labor market, they decrease the amount of time spent with their child, but this is compensated by an increase in the spouse's time with their child.

Table D.1: Time investments and labor supply (2010)

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

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

The measure of effort is constructed via Principal component analysis, extracting one factor for the variables used as measures of time investments by parents. The measures of parental effort, together with the big five personality test scores and the Wais cognitive assessments are all standardized to have mean zero and one standard deviation. In the regression the measure of effort is in hundreds.

Table D.2: Time investments and labor supply (2012)

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

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

The measure of effort is constructed via Principal component analysis, extracting one factor for the variables used as measures of time investments by parents. The measures of parental effort, together with the big five personality test scores and the Wais cognitive assessments are all standardized to have mean zero and one standard deviation. In the regression the measure of effort is in hundreds.

Table D.3: Regressions of effort in differences

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

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

$\Delta X = X_{2012} - X_{2010}$. The measure of effort is the same used as in Table D.2 but in differences. The same controls as in Table D.2 are used.

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

E Distribution of Childcare providers

Figure E.1 reports the distribution of institutions within a neighborhood (within 5km from household) as well as the distance to the nearest preschool provider from households.

Figure E.1: Information on Preschool Providers

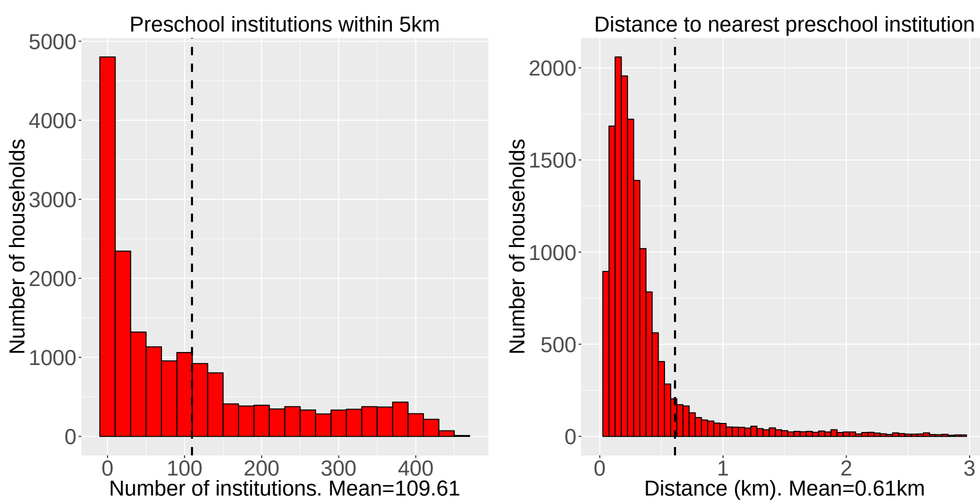


Figure E.2 is an example of the distribution of childcare and preschool providers in the City of La Serena, Chile.

Figure E.2: Example of distribution of childcare providers. City of "La Serena", Chile

F Cash Transfer Programs in Chile

The basic program through which poor families receive cash transfers from the central government is the "Unique Family Subsidy".[28] Such program established a monthly transfer of $14,340 CLP in 2012, for a family in conditions of vulnerability[29] with one child.[30] 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.[31]

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

[28]Subsidio Unico familiar in Spanish.

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

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

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

implemented the implemented the “Permanent Family Contribution Program”. In 2016, those families who were eligible to either “Unique Family Subsidy” or “Family Assignments” were automatically eligible to be part of the “Permanent Family Contribution Program”. which consisted in a transfer of $43,042 anually for each children and one for the family as a whole. Thus, a family one child would be eligible to receive $86,084 CLP.

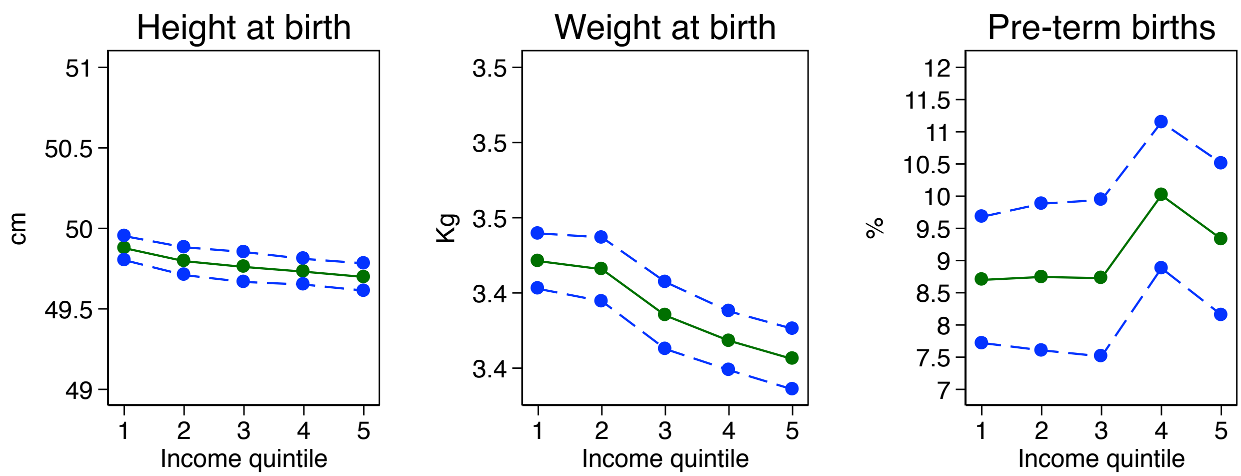
Overall, a family of one child that was receiving transfers from the “Unique Family Subsidy” program in 2012, would see an increase in the monetary transfers from the central government equivalent to 72.8% in real terms.

G Reduced-form Evidence

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

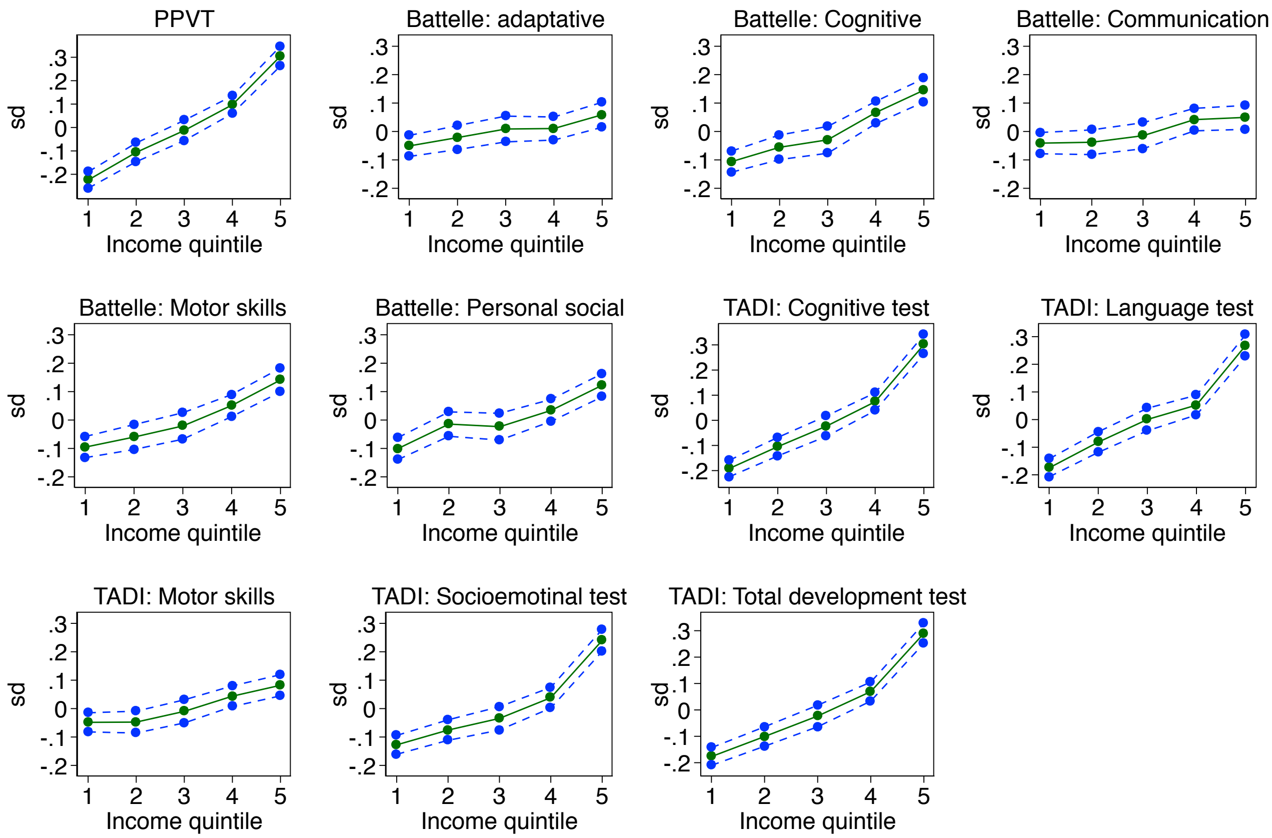
G.1 Gaps in skills emerge early in life

Figure G.1: Gaps in health at birth



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

Figure G.2: Gaps in skills at age 5



The green (solid) line is the mean score, the blue (dashed) line is the 95% confidence interval. All test scores and parental assessments are normalized to have mean zero and variance one. PPVT stands for Peabody Picture Vocabulary Tests. Battelle is an instrument containing different scales to measures development of children. TADI is a test of learning and child development[a]. In all tests, differences between the scores of children in the lowest quintile of the income distribution is statistically different to those children who are in the highest quintile of the income distribution.

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

When analyzing height at birth, weight at birth and the incidence of pre-term births[32], for different income groups, we do not observe dramatic differences between poor and rich children, as can be seen in Figure G.1. However, we do observe differences in various dimensions of development, such as vocabulary, communication skills, motor skills and cognitive achievement, when children are five years old. This can be seen in Figure G.2. The figure reports the scores in different tests and parental assessments. All of them are standardized to be mean zero and

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

variance one. We see, for instance, that children in the lowest income quintile score 0.1 of a standard deviation below the mean on the Battelle test score for Motor Skills, whereas children in the richest quintile score 0.15 of a standard deviation above the mean. The most dramatic case is vocabulary, where children in the lowest income quintile score 50% of a standard deviation below children located in the richest income quintile. This early emergence of gaps in the development of children is consistent with the literature (Schady et al., 2015; Cunha et al., 2010).

G.2 Female empowerment and child outcomes

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

We do observe evidence of a positive relationship between female empowerment and child outcomes. Table G.1 presents the results of various regressions showing positive correlations between child outcomes and the share of income earned by women. Even after controlling for variables such as the IQ level of the primary caregiver, total household income, grades of schooling of both parents and their ages, we observe a positive relationship between the share of the total household income earned by mothers and children's outcomes.

When analyzing the responses to the female empowerment questionnaires, we also observe a positive relationship between female empowerment and investments in children. In Table G.2, some regressions of child investments and female empowerment are presented. I show again that, even after controlling for the same variables as mentioned before, those households where women are relatively less empowered make fewer investments in their children. Those households where the woman manages the income are more likely to have toys for the development of children, and the frequency of consumption of fruits and vegetables is higher whereas that of bread is smaller. Similarly, households that are more accepting of the opinion that women should not work and should exclusively take care of their children are more likely to have the children sharing their bed with someone else, which might be an indicator of lower investments in children.

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

Table G.1: 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	0.09*	0.09*	0.10**
	(0.05)	(0.05)	(0.05)
Total household income	0.00	0.00**	0.00**
	(0.00)	(0.00)	(0.00)
Mother's years of schooling	0.01**	0.02***	0.03***
	(0.01)	(0.01)	(0.01)
Father's years of schooling	0.02***	0.01**	0.02***
	(0.01)	(0.01)	(0.00)
Number of siblings	0.02	-0.00	-0.03*
	(0.01)	(0.01)	(0.01)
Age of child (months)	0.00***	0.00***	0.01***
	(0.00)	(0.00)	(0.00)
BFI-Extraversion	0.06***	0.04**	0.04***
	(0.02)	(0.02)	(0.02)
BFI-Kindness	-0.00	0.09***	0.02
	(0.02)	(0.02)	(0.02)
BFI-Responsibility	0.10***	0.08***	0.07***
	(0.02)	(0.02)	(0.02)
BFI-Neuroticism	-0.02	-0.03*	-0.01
	(0.02)	(0.02)	(0.02)
BFI-Openness	0.07***	0.03	0.03
	(0.02)	(0.02)	(0.02)
Wais-digits	0.01	0.01	0.02***
	(0.01)	(0.01)	(0.01)
Wais-Vocabulary	0.00	0.00***	0.00***
	(0.00)	(0.00)	(0.00)
Observations	6,823	6,823	6,822
Adjusted R-squared	0.03	0.05	0.08

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

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

Table G.2: Female empowerment and Child outcomes

VARIABLES	(1) Toys for development	(2) Fruits and vegetables	(3) People sharing bedroom with child
Total household income	0.00***	0.00	-0.00***
	(0.00)	(0.00)	(0.00)
Mother's years of schooling	0.01***	0.01**	-0.03***
	(0.00)	(0.01)	(0.00)
Father's years of schooling	0.01***	0.01**	-0.02***
	(0.00)	(0.00)	(0.00)
Number of siblings	0.00	0.04**	0.08***
	(0.01)	(0.01)	(0.01)
People in household	-0.01**	0.01	0.13***
	(0.01)	(0.01)	(0.01)
Woman administers+	0.03**	0.09***	-0.00
	(0.01)	(0.02)	(0.02)
Gender roles -Woman++	-0.01	-0.03**	0.02*
	(0.01)	(0.01)	(0.01)
Gender roles - Man++	-0.01	-0.05*	0.06**
	(0.01)	(0.03)	(0.02)
Observations	6,344	8,245	8,246
Adjusted R-squared	0.04	0.03	0.19

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

Consumption of bread, fruits and vegetables and cookies and candies is related to the frequency of consumption of this food on a weekly basis. More details can be found in Table 7. + 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”.

H Smoothing distribution

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

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

$$f(K_t|O_{0:2}) \tag{68}$$

where we basically condition on all the measures we have. Note that we can write Equation 68 as:

$$f(K_t|O_{0:2}) = f(K_t|O_{0:t}) \int \left(\frac{f(K_{t+1}|O_{0:2}) f(K_{t+1})}{\int f(K_{t+1}) f(K_1|O_{0:t}) dK_t} \right) dK_{t+1} \tag{69}$$

And then we can approximate this distribution $\hat{f}(K_t|O_{0:2})$ by getting $rr = 1..RR$ draws according to:

$$\hat{f}(K_t|O_{0:2}) = \sum_{rr=1}^{RR} w_{t|T}^{(rr)} \delta_{K_t^{(rr)}}(K_t) \tag{70}$$

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

$$w_{t|T}^{(mm)} = w_t^{(mm)} \left[\sum_{rr=1}^{RR} w_{t+1|T}^{(rr)} \left(\frac{f\left(K_{t+1}^{(rr)}|K_t^{(mm)}\right)}{\sum_{kk=1}^{KK} w_t^{(kk)} f\left(K_{t+1}^{(rr)}|K_t^{(kk)}\right)} \right) \right] \tag{71}$$

where $w_{T|T} = w_T$

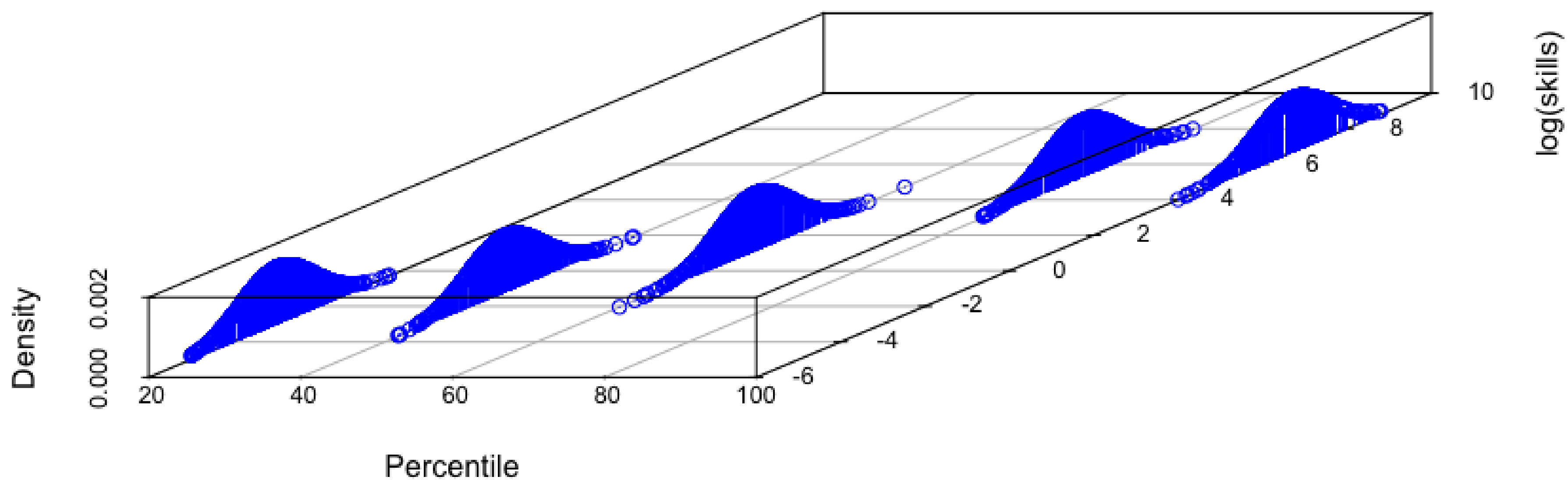
Smoothing algorithm

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 $rr = 1 \ldots RR$

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

Figure H.1: Smoothing Distribution of Skills According to Household's Income Percentile



The distribution of $log(skills)$ is plotted for representative households. Households located in the 20th, 40th, 60th, 80th and 100th percentile of total household income. The smoothed distribution of all the households is presented in Figure 3

I Signal to Nose ratio

Table I.1: Maternal effort 2012

Measure	Signal (%)
Teaches her words	95.94
numerical activities	95.73
Teaches colors	35.58
Teaches animals and their sounds	32.52
chatting or drawing	13.67
household chores	12.41
Sings to child	10.32
supermarket	9.24
Visit friends-family	8.93
Reads to child	7.28
Shares a meal	7.07
Tells her stories	6.47
Takes her to parks	3.85
Takes her to museums-zoo-park	2.56

Table I.2: Paternal effort 2012

Measure	Signal (%)
Teaches her words	96.94
numerical activities	96.78
Teaches colors	42.59
Teaches animals and their sounds	39.29
chatting or drawing	17.53
household chores	15.99
Sings to child	13.39
supermarket	12.02
Visit friends-family	11.64
Reads to child	9.54
Shares a meal	9.27
Tells her stories	8.50
Takes her to parks	5.10
Takes her to museums-zoo-park	3.41

Table I.3: Maternal effort 2010

Measure	Signal (%)
Spends time with her talking or drawing	66.43
Plays with her	30.33
Sings to her	20.86
Reads Childre's storybooks or drawing books	19.01
Tells her stories	14.37
Takes her to parks, museums, zoos, libraries or other cultural activities	13.96

Table I.4: Paternal effort 2010

Measure	Signal (%)
Spends time with her talking or drawing	72.66
Plays with her	36.90
Sings to her	26.14
Reads Childre's storybooks or drawing books	23.97
Tells her stories	18.40
Takes her to parks, museums, zoos, libraries or other cultural activities	17.89

Table I.5: Investments 2010

Measure	Signal (%)
Child has at least one toy that involves muscular activity	83.50
Child has at least one toy with wheels	75.78
Child has toys to pull and push	72.95
Child has a special place where to store toys and belongings	49.40
Availability of musical or literary toys	38.25
Availability of plush toys-stuffed animals	32.57
Child has three or more books of his own	19.19
Availability of mobiles for child	9.98

Table I.6: Investments 2012

Measure	Signal (%)
There are two or more toys in the household that can help with learning numbers	99.98
There are two or more toys for free expression or impersonations such as tools and customs	99.97
Child has three or more puzzles	26.37
At first sight, there is very little evidence that there is a child living in the household	24.39
There are two or more toys in the household where child can learn colors, sizes and shapes	20.76
There are at least ten books for adults	18.49
There is a music device where child can listen children's music	16.27
There are at least ten children's books available in the house	4.35
Number of people with whom child shares bed	1.40
Number of people with whom child shares room	1.26
Consumption of juice*	1.25
Consumption of milk*	0.53
Consumption of fruits and vegetables*	0.34
Consumption of Chocolate-Candy*	0.26
Consumption of legumes*	0.22
Consumption of cookies*	0.19
Consumption of Fish-Beef-Chicken*	0.16
Consumption of water*	0.10
Consumption of hamburger-pizza-fries*	0.04
Consumption of bread-rice-pasta	0.00
Consumption of snacks in bags*	0.00

*: 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 I.7: Health at birth

Measure	Signal (%)
Cigarrettes consumed during pregnancy	100.00
Substance abuse during pregnancy*	100.00
Alcohol consumption during pregnancy*	99.98
Cigarrettes consumed during the first six months of life of child	99.97
Mother diagnosed with Depression during pregnancy	98.68
Mother diagnosed with Obsesive compulsive D. during pregnancy	98.13
Mother diagnosed with Fobia during pregnancy	97.07
Mother diagnosed with Hemorrages during pregnancy	94.94
Mother diagnosed with Toxoplasmosis during pregnancy	94.26
Mother diagnosed with Preeclampsia during pregnancy	94.17
Mother diagnosed with Placenta Previa during pregnancy	93.93
Mother diagnosed with Cholestasis during pregnancy	93.43
Child was born pre-term	91.73
Mother diagnosed with Anemia during pregnancy	88.98
Mother diagnosed with Anxiety D. during pregnancy	86.66
Mother diagnosed with Urinary infections during pregnancy	83.93
Mother diagnosed with Panic D. during pregnancy	82.63
Mother diagnosed with PTSD during pregnancy	82.33
Mother diagnosed with Hipertension during pregnancy	76.81
Mother diagnosed with Bipolar D. during pregnancy	71.58
Mother diagnosed with Diabetes G during pregnancy	68.55
Weight at birth (grams)	13.80
Height at birth (cm)	1.81

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

Table I.8: Skills 2010

Measure	Signal (%)
CBCL-Aggressive behavior	99.84
CBCL-Emotional intelligence	9.66
CBCL-Attention deficit	7.13
CBCL-anxiety -depression	6.34
CBCL-Isolation	3.83
CBCL-Sleeping disorder	2.90
CBCL-somatic complaints	2.33
TEPSI-Coordination subdomain	0.67
TEPSI-Language subdomain	0.41
TEPSI-Motor skills subdomain	0.31

Table I.9: Skills 2012

Measure	Signal (%)
Battelle-Cognitive	52.09
Battelle-Motor	50.07
Battelle-Comunication	44.71
Tadi-Language	42.30
Tadi-Cognitive	37.89
Tadi-Socioemotional	36.73
Battelle-Personal-Social	32.98
Tadi-Motor	30.89
Battelle-Adaptative	29.45
PPVT-Vocabulary	27.63

Table I.10: Pareto weight

Measure	Signal (%)
Women should work full time and delegate childcare to a third party	81.27
Men are the best suited to take care of children	81.14
Women should take care of chidlren and work part time	44.08
Both, father and mother, decide how to spend income	34.80
Mothers should take care of children	32.66
Women's only activity should be taking care of children	29.47
Father decides how to spend income	12.05
A woman who is in charge of most part of tasks of the household has no time to work*	5.77
Fathers should take care of chidlren	5.75
After having children, the best for a woman is to develop her carreer*	2.23
If my spouse earned enough there is no reason for me to work*	1.85
Having a payed job is very important in life*	1.36
Fathers time is as important as mothers time for child development*	1.12
Both spouses should contribute to household income*	0.98
Mother decides how to spend income	0.76
Men should go to work and women should stay home*	0.62
It is better to have a bad marriage than to remain single*	0.11
Men should participate in household chores more actively than they actually do*	0.03
Having a payed job is the best way for a woman to become independent*	0.03

*: 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.

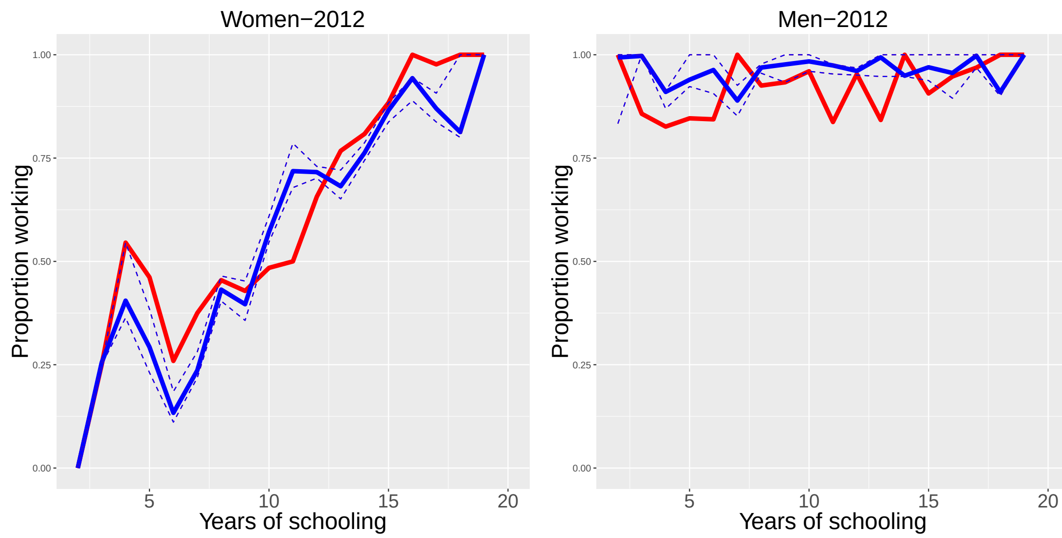
Table I.11: Skills of primary caregiver

Measure	Signal (%)
BFI-Openness	23.60
BFI-Extroversion	22.94
BFI-Neuroticism	21.76
WAIS-Vocabulary test	18.70
BFI-Conscientiousness	17.24
BFI-Agreeableness	12.73
WAIS-Numerical test	10.71

J Bootstrap model fit

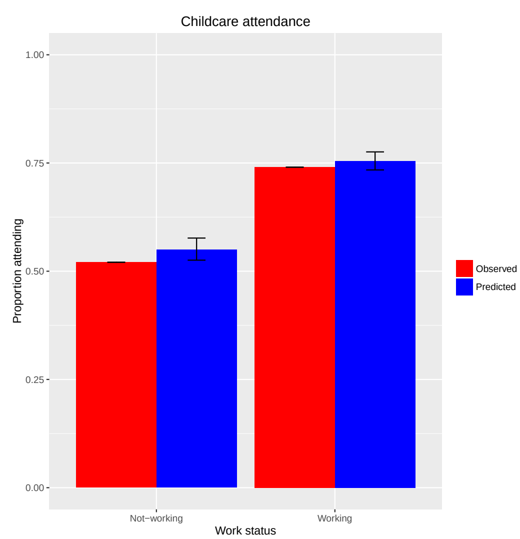
The model fit presented in the main body of the paper is done by setting all the shock levels equal to their mean value. Alternatively, a model fit can be reported by getting the corresponding draws from the distribution of the shocks. In this subsection, I report the results of the model fit when, rather than setting the shocks at their mean values, I draw from their distribution. This allows me to obtain a distribution of the relevant variables for the model fit. Figure J.1 I report the bootstrap fit of labor force participation for women and men in 2012. Figure J.2 reports the corresponding distribution for childcare demand. As can be seen from both figures, in the case of the bootstrap fit, the model does a good job fitting the observed levels.

Figure J.1: Bootstrap fit: Parents' Labor Force Participation in 2012



Dashed lines represent the 95% confidence interval

Figure J.2: Bootstrap fit: Childcare decisions (%)



Brackets include the 95% confidence interval

K Child Investments and Bargaining Power

As shown in the Reduced-form evidence, women spend more time with their children even when controlling for labor supply. This, together with the evidence that cash in the hands of women translates into better child outcomes than cash in the hands of men, is often used as evidence that women have stronger preferences for children and thus monetary transfers should be given to women if the objective is to invest more in children. Nonetheless, this evidence is explained by several other factors.

First of all, mothers' time seems to be more productive than fathers' time, as shown by the estimation results of the model. Additionally, mothers have stronger preferences for children and the utility penalty of time investments is lower for mothers than for fathers. However, in addition to these facts, the relative empowerment of each member distorts time decisions, which explains part of the differences in time investments. Given that both parents are making investments in a public good (skills of their child) and that effort is costly and privately exerted, the fact that women spend more time with children is also a consequence of their relative disempowerment in the household rather than simply a result of different preferences.[33]

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

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

$$\max_{e^f, e^m} s_2(e^f, e^m, .) \text{ subject to } e^f + e^m = e^{f,*} + e^{m,*} \tag{72}$$

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

where $e^{j,*}$ is the optimal solution to the maximization of the household welfare problem described in Equation 7. Define the solution to the problem in 72 as $\left(e^{f,c_1}, e^{m,c_1}\right)$.

Similarly, we can define an alternate centralized problem where we maximize skills subject to the fact that the total time-cost exerted in the production of skills should not exceed that found in the household's problem defined in 2-**??**. Formally:

$$\max_{e^f, e^m} s_2(e^f, e^m, .) \text{ subject to } c\left(e^f\right) + c\left(e^m\right) = c\left(e^{f,*}\right) + c\left(e^{m,*}\right) \tag{73}$$

where the cost of effort is given by $c^j(e^j) = \alpha^j_{4,2} e^j (1 + h^j)$. I call the solution to 73 $\left(e^{f,c_2}, e^{m,c_2}\right)$. In both cases, for $l = 1, 2$, we do find that:

$$\frac{\left(\frac{e^{f,c_l}}{e^{m,c_l}}\right)}{\left(\frac{e^{f,*}}{e^{m,*}}\right)} \propto \left[\frac{(1-\mu)}{\mu}\right]^{\phi/(1-\phi)} \tag{74}$$

The difference of ratios of effort in the centralized solutions and in the household problem originally defined in 2-**??** depends on the Pareto weight and the degree of substitutability between parental efforts. If the Pareto weight heavily favors one member, and if there is some degree of substitutability between parental effort, there would be an inefficient allocation in time investments given that we can find an alternative allocation with the same amount of cost, or the same amount of total effort, that will yield better child outcomes. I find that this mechanism explains 15% of the differences in time investments between mothers and fathers.

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

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