Parental Investments and Intra-household Inequality in Child Development: Theory, Measurement, and Evidence from a Lab-in-the-Field Experiment

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Abstract

This paper studies intra-household inequality in child human capital by combining a theoretical model of household behaviour with a lab-in-the-field experiment. The model highlights the key role that parental investments have to explain inequality in child outcomes and how these investments depend on preferences, beliefs and financial constraints. To mitigate the identification problem posed by observational data, I use a novel survey methodology based on hypothetical scenarios to collect data on subjective expectations and stated choices with and without financial constraints. I find that parents have a low aversion for inequality in child outcomes. Because they perceive the returns to investments to be larger for children with higher initial conditions, they allocate more resources to children with higher levels of human capital. Resources are also important, as credit-constrained parents select more unequal allocations. I show that structural parameters identified in the experiment are predictive of *actual* investment behaviour. The findings suggest that early levels of human capital have a key role in driving inequality both within and between households.

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1 Introduction

Intra-household inequality is key for the understanding and the measurement of poverty and inequality (Chiappori & Meghir (2015); Brown, Ravallion, & Van De Walle (2017)). This paper focuses on inequality in human capital outcomes *between* children living in the same family. Because the early years are critical for the process of human capital formation and can have important consequences for well-being through the life cycle ((Currie & Almond (2011); Brito & Noble (2014); Heckman & Mosso (2014)), understanding the origin of this inequality is key to the design of effective policies that aim at reducing inequality across individuals. In particular, if intra-household inequality between children is driven by parental choices, understanding what determines these choices can help policy-makers design better interventions that account for parents' endogenous responses.[1]

To study the sources of intra-household inequality in child outcomes, in this paper I combine a theoretical model of household behaviour with experimental data from India. I use the theoretical framework to motivate the empirical analyses, design the survey strategy and measurement tool, and interpret the empirical findings. The model fleshes out the separate role that parental preferences, beliefs and financial constraints have in determining household choices, highlighting the challenge that the use of observational data poses to the identification of key parameters and mechanisms of interest. The reason for this challenge is a twofold identification issue. First, realized choices may be consistent with many alternative specifications of preferences and beliefs (Manski (2004)). Second, credit constraints might prevent parents from selecting their preferred choices, breaking the direct connection between observed outcomes and parental preferences. Guided by this theoretical framework, I design and implement a lab-in-the-field experiment that allows me to overcome these identification challenges. I develop a novel survey methodology based on hypothetical scenarios to elicit direct measures of parental beliefs, identify preferences for intra-household inequality, and study the role that credit constraints have to determine choices. I then show that structural parameters identified in the experiment are predictive of *actual* parental behaviour.

The theoretical analysis builds on the conventional literature on intra-household resource allocation. Inequality arises through two distinct channels. The first is a biological channel operating through the production function for human capital: Siblings are born with different initial conditions – or endowments – and these endowments have a direct effect on child human capital (Behrman & Rosenzweig (2004); Royer (2009); Almond & Mazumder (2011); Figlio, Guryan, Karbownik, & Roth (2014)). The second channel operates through parental allocations of resources (Becker & Tomes (1976); Behrman, Pollak, & Taubman

[1] Relatedly, recent work has documented that intra-household inequality between children and adults has important consequences for child poverty (Dunbar, Lewbel, & Pendakur (2013)).

(1982); Behrman (1988); Pitt, Rosenzweig, & Hassan (1990)). By differentially investing in their children, in ways that reinforce or compensate initial differences, parents may exacerbate or attenuate the biological effect of endowments.

I extend this analysis in two ways. First, I allow parents to have inaccurate beliefs about the production function for child human capital. The standard practice in economics to investigate what drives parental allocations, is to focus on the interplay between the technology of skill formation and parental preferences for intra-household inequality. The implicit assumption underlying these models is that parents have full knowledge of the process of child development when making these decisions. Previous work has therefore relied on allocations data to derive conclusions on the nature of parental preferences (Behrman, Pollak, & Taubman (1982)). Given the great difficulties in identifying the properties of the human capital production function, it seems likely that parents make investment choices based on imperfect information. Indeed, recent evidence suggests that parents hold inaccurate beliefs about the productivity of different inputs entering the production function for child human capital, and are mistaken about important features of the process of human capital accumulation (Boneva & Rauh (2018); Attanasio, Cunha, & Jervis (2019)).[2]

Second, I extend the analysis to examine how household resources affect allocation choices. Traditional models assume that parents have sufficient resources to adequately investing in the human capital of *all* their children. This might be particularly problematic in larger families, where per-capita resources are lower.[3] I show that when children have heterogeneous endowments, an increase in family size will result in lower per-capita resources, and may lead to the reallocation of resources differentially across children, increasing the overall level of inequality in a family. This result underscores the key role that financial constraints might have to explain parental human capital investments and intra-household inequality.

By incorporating these frictions into a standard model of intra-household allocation of resources, I show that identification issues are of first order importance: Beliefs and financial constraints are usually not observed in standard survey data. Therefore observational data on parental allocative choices do not allow to separate their role from that of preferences. Clearly, these distinctions are crucial to understand the sources of intra-household inequality, and to the design of policies that could effectively tackle it.

Guided by the theory, I design a novel measurement strategy based on hypothetical scenarios that

[2]There is also evidence that parents might have inaccurate perceptions about their children's human capital, causing the mis-allocation of education investments (Dizon-Ross (2019)). The theoretical framework that I present in the following sections can be easily extended to allow for this possibility. Moreover, the empirical strategy that I use is robust to the possibility that parents might have inaccurate beliefs about their children's human capital.

[3]The idea that parental investments might be affected by family size goes back to the seminal Quantity-Quality (Q-Q) model by Becker & Lewis (1973), which predicts that decreases in fertility will induce more resources to be allocated to each child so that average levels of child human capital will increase. Importantly, this model rests on the implicit assumption that the quality of each child is the same.

allows me to elicit parental beliefs about the human capital production function, and identify preferences for intra-household inequality. I embed this innovative measurement tool in a lab-in-the-field experiment with parents of primary school children in India. The experiment consists of two stages. I the first stage, I identify parental beliefs about the human capital production function. The approach used to elicit these beliefs builds on the work by Cunha, Elo, & Culhane (2013), Boneva & Rauh (2018) and Attanasio, Boneva, & Rauh (2019). It consists in presenting a series of hypothetical stories to the respondent and elicit information on individual expectations about certain events. By varying the characteristics of the scenarios one at a time while keeping other factors constant, one can identify the perceived returns to different inputs. Following the theoretical model, I focus on the role of perceived returns to child endowments and parental investments, and on their perceived complementarity or substitutability, as these are the key parameters that matter for the allocative decision. To elicit these perceived returns, parents are asked to state what they expect the future earnings of the child will be at age 30.

Having identified parental beliefs about the human capital production function, I the second stage of the experiment I collect parents' stated choices (Mas & Pallais (2017); Wiswall & Zafar (2018); Adams-Prassl & Andrew (2020); Ameriks, Briggs, Caplin, Shapiro, & Tonetti (2020)). As in the case of beliefs, respondents are presented with hypothetical scenarios. But in this stage of the experiment, instead of asking respondents to report what they believe the outcome of the child would be, I ask them to select their favourite allocation choice. The design of the scenarios closely follows the theoretical framework. In particular, because the model highlights that investments might depend on child endowments and household resources, scenarios vary according to these two key dimensions. Combining the structure of the model with experimental data on beliefs and choices, I can isolate parents' preferences at the time of the survey, free from other confounding factors. Importantly, because scenarios vary in terms of resources available to the family, I can also study the separate role that credit constraints have in determining allocative decisions. By directly eliciting information about the *perceived* production function, I can avoid making strong assumptions on parental information sets and beliefs, upon which earlier work relies.[4,5]

[4]See Ayalew (2005); Rosenzweig & Zhang (2009); Datar, Kilburn, & Loughran (2010); Aizer & Cunha (2012); Del Bono, Ermisch, & Francesconi (2012); Hsin (2012); Bharadwaj, Eberhard, & Neilson (2018)).

[5]While not directly designed to understand the sources of intra-household inequality in child outcomes, in independent work developed contemporaneously to this paper Berry, Dizon-Ross, & Jagnani (2020) (BDJ) also use a lab-in-the-field experiment to study parental preferences for investing in their children. There are a few important differences between BDJ and this paper. Rather than using data on parental *actual* beliefs about the production function, BDJ shocks to the short run returns to investing in children for identification. There are advantages and disadvantages for each of these two identification strategies. On the one hand, the strategy in BDJ does not allow studying the role that individual perceived returns about various inputs have in explaining household behaviour. Moreover, changing the child specific payments functions that map child test scores to final outcomes might challenge the external validity of the results, as the way parents make allocation choices might be affected by the environment where those decisions are made. (E.g. an environment that highly rewards test score points might give an incentive for parents to reward the child they perceive to be the highest achiever). BDJ also does not explicitly study the role of credit constraints for parental investment decisions. As I discuss later, constraints play

Several key results emerge from this study. First, I find that parents perceive endowments and investments to be highly productive. A one-standard-deviation increase in endowments is perceived to increase earnings by 15 percent; a similar increase in investments boosts adult earnings by 28 percent. Moreover, parents perceive investments and endowments to be complements i.e. they believe that investments are more productive for children with higher initial conditions. This perceived complementarity generates an incentive for parents to reinforce initial differences across their children. Interestingly, I also document a substantial amount of heterogeneity in perceived returns. By showing that parental beliefs about the human capital production function matter for intra-household allocations, I contribute to a growing literature focusing on the role of subjective expectations as a determinant of human capital investment decisions.[6] I advance this literature by documenting that perceived returns matter to explain differences in investments *within* a family across children, beside their well documented importance to explain inequalities *between* families (Boneva & Rauh (2018); Attanasio, Cunha, & Jervis (2019)).

Second, the experimental results reveal that parents are not averse to inequality over their children's human capital outcomes and reinforce differences in initial endowments. Specifically, I show that when the difference in child initial conditions increases parents re-allocate resources towards the higher achieving child, suggesting that parents investment choices are to some extent driven by efficiency considerations (Becker & Tomes (1976); Griliches (1979); Behrman, Pollak, & Taubman (1982); Behrman (1988); Pitt, Rosenzweig, & Hassan (1990)). As in the case of beliefs, I find heterogeneity in parental preferences, with some parents being significantly less inequality averse than others.

Third, I show that financial resources are important in explaining household choices. In particular, I find that parents reinforce more strongly initial conditions and select more unequal allocations in scenarios when resources are low compared to the high-resources scenarios. This result adds to and complements a large literature investigating the role that credit constraints have to explain socio-economic gaps in school enrolment and educational investments (Lochner & Monge-Naranjo (2012); Kaufmann (2014); Solis (2017)). I contribute to this literature, by presenting evidence that credit constraints have important implications for the *allocation* of human capital investments across siblings. In particular, the results reveal that credit-constraint households reinforce more strongly, resulting in more intra-household inequality. Relatedly, the results imply that by reducing per-capita resources, family size affects the allocation of

a key role to explain the distribution of child human capital in the household. On the other hand, controlling the production function that maps choices to final outcomes allows BDJ to consider the possibility that parents have a preferences for equalizing the inputs allocated to their children, rather than their final outcomes. This is not possible in the context of the current experiment.

[6] See Attanasio & Kaufmann (2009); Jensen (2010); Arcidiacono, Hotz, & Kang (2012); Attanasio & Kaufmann (2014); Stinebrickner & Stinebrickner (2014); Wiswall & Zafar (2015); Boneva & Rauh (2017); Delavande & Zafar (2019).

resources across children, resulting both in lower levels of *average* child quality and exacerbating intra-household inequality within the family.

More broadly, by demonstrating how important factors that have been show to matter for inequality in child outcomes *across* households are also key to inequality within the family, this paper relates to a growing body of evidence pointing at the importance of intra-household inequality to understand differences across individuals.[7] While the traditional focus of this literature is the measurement of inequality across different groups of individuals living in the household (e.g. men *vs.* women; adults *vs.* children), I document the importance of intra-household inequality between siblings' human capital outcomes and propose a mechanism that explains the existence of intra-household inequality: Both the model and the empirical findings suggest that child endowments have a key role in driving inequality in child outcomes.

Finally, in terms of field methodology, this paper relates to a growing literature using hypothetical scenarios to collect data on individual beliefs, and elicit stated choices to understand behaviour.[8] I show how strategically designed, theory-driven survey measures can be combined to identify structural parameters of interest. One implicit assumption about this methodology is that stated choices reported in the experiment are reflective of what respondents would do in actual scenarios, i.e. that elicited preferences relate to *actual* household behaviour. Growing evidence points to the fact that the two approaches of using stated choices or actual choices yield similar preference estimates in a variety of contexts, especially when the hypothetical scenarios are realistic and relevant for the respondents (Mas & Pallais (2017); Wiswall & Zafar (2018)). To address this question, I collect data on *actual* educational investments made by parents. I find a strong systematic relation between elicited preferences and realized investments. In particular, respondents that are identified as less inequality averse in the experiment, spend more unequally on their children's education. I also find that higher endowment children are more likely to attend a private school and less likely to work, suggesting that these decision extend beyond educational expenditure at a particular point in time with potentially important longer-term effects. These results add credibility to the research design and to the use of hypothetical scenarios to identify structural parameters of interest.

The remainder of the paper is organized as follows. In the following section, I present some basic stylized facts that provide the motivation for the study. Section 3 present a simple conceptual framework

[7]See Haddad & Kanbur (1990); Lise & Seitz (2011); Dunbar, Lewbel, & Pendakur (2013); Chiappori & Meghir (2015); Brown, Ravallion, & Van De Walle (2017); Brown, Calvi, & Penglase (2020); Calvi (2020).

[8] Cunha, Elo, & Culhane (2013), Attanasio, Boneva, & Rauh (2019), Boneva & Rauh (2018), Attanasio, Cunha, & Jervis (2019) elicit data on parental beliefs about the child human capital production function. Importantly, these papers do not use these data to identify parental preferences. Mas & Pallais (2017), Wiswall & Zafar (2018), Adams-Prassl & Andrew (2020), Ameriks, Briggs, Caplin, Lee, et al. (2020), Ameriks, Briggs, Caplin, Shapiro, & Tonetti (2020), use stated choice data to study preferences for workplace attributes, university choices, marriage markets, saving behaviour and labour force participation.

that can be used to study intra-household inequality in child outcomes. Section 4 describes the measurement tools and the experimental design. Section 5 describes the setting and the data. I discuss the results in section 6. Section 7 concludes.

2 Motivating Evidence

The basic empirical evidence motivating this study is presented in Figure 1. This figure plots the shares of total variation in child educational attainment that can be attributed to the within- and between-households components. To perform this decomposition, I use the Mean Log Deviation (MLD) measure of inequality (Ravallion (2015)), which can be exactly separated into a within-group and a between-groups components.[9] The figure shows that intra-household variation explains between 30 to 45 percent of overall inequality in child human capital. In India, the country under study in this paper, inequality between siblings amounts to 33 percent of overall inequality in child outcomes (similar results for age-standardized test scores are reported in Appendix Figure A.1).

In panel A of Figure 2, I plot the same relation but stratifying the sample by family size. In particular, the figure show the intra-household contribution to overall inequality separately for families with a different number of children. The figure reveals that the share of variance in child human capital explained by within-household variation rises from 25 percent in a two-children family to 70 percent in families with six or more children. To study what explains this large increase, in panel B of Figure 2 I plot the human capital distribution by family size, focusing on the mean, the maximum, and the minimum of the distribution (i.e. the human capital of the highest and lowest-achieving child, and the average level of human capital in the family). This figure reveals several interesting patterns.

First, intra-household inequality increases with family size. Second, this increase can be almost entirely explained by a large drop at the bottom of the human capital distribution. Specifically, as family size increases: (i) there is a steep drop-off in the minimum level of human capital; and (ii) a shallow gradient in the maximum level of human capital, so that the outcomes of low-achieving children are very sensitive to variations in family size, while high-achieving children are largely unaffected. Third, as predicted by the Q-Q model, there is a negative relationship between average child quality and family size. I report several robustness checks for this relation in Appendix C. In particular, I show that these patterns are very robust across countries and to the use of alternative measures of child human capital. Moreover, this relation holds controlling for family and child characteristics. In particular, it is not driven by birth

[9] See Appendix B for details about the MLD measure of inequality, and its decomposition.

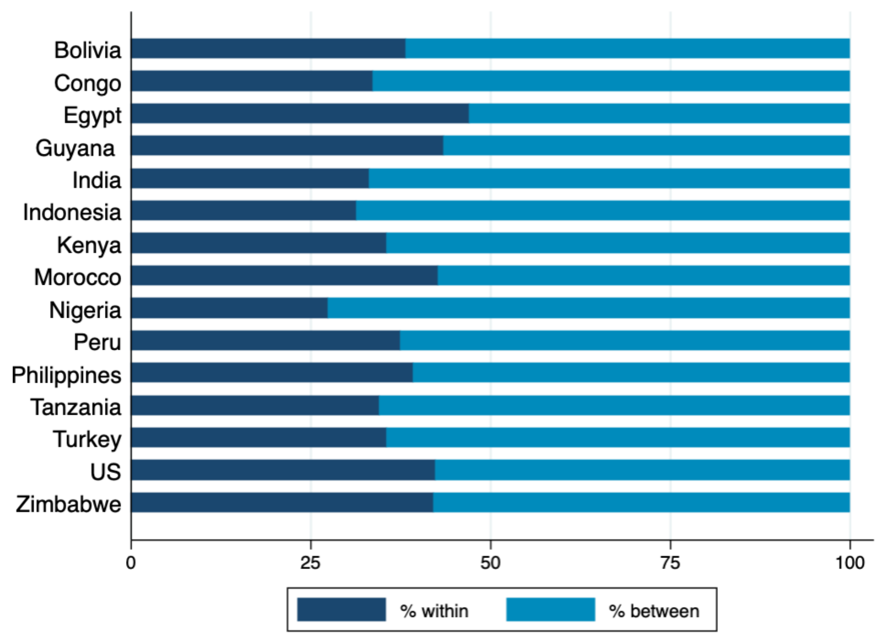


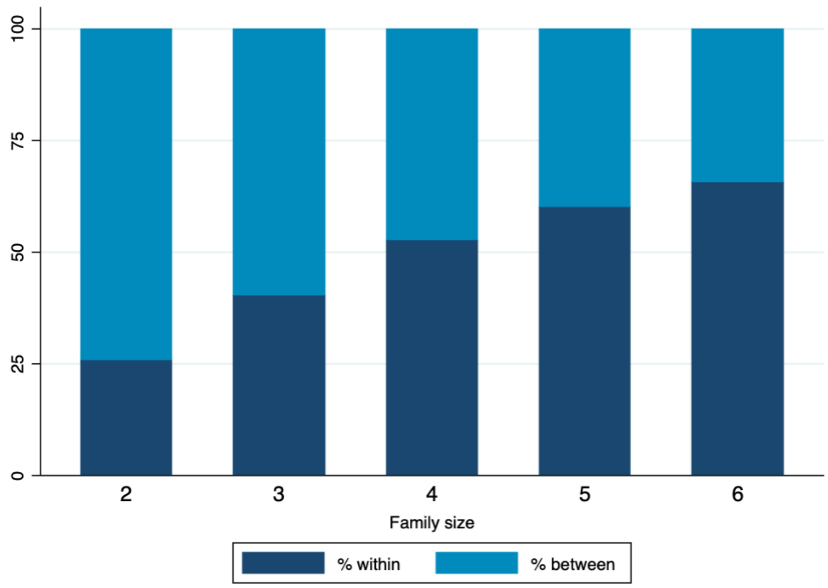
Figure 1: Inequality in Child Human Capital

Notes: This figure plots the within-household and between-households component of the Mean Log Deviation (MLD) measure of inequality. The outcome variable is educational attainment. I use an age-standardized z-score, where the reference group consists of children in the same country and birth cohort. Thus coefficients are expressed in standard deviations units. Each bar represents a different country. Source: Development and Health Survey (DHS), for the US Children for the National Longitudinal Survey of Youth 1979 (NLSY-79).

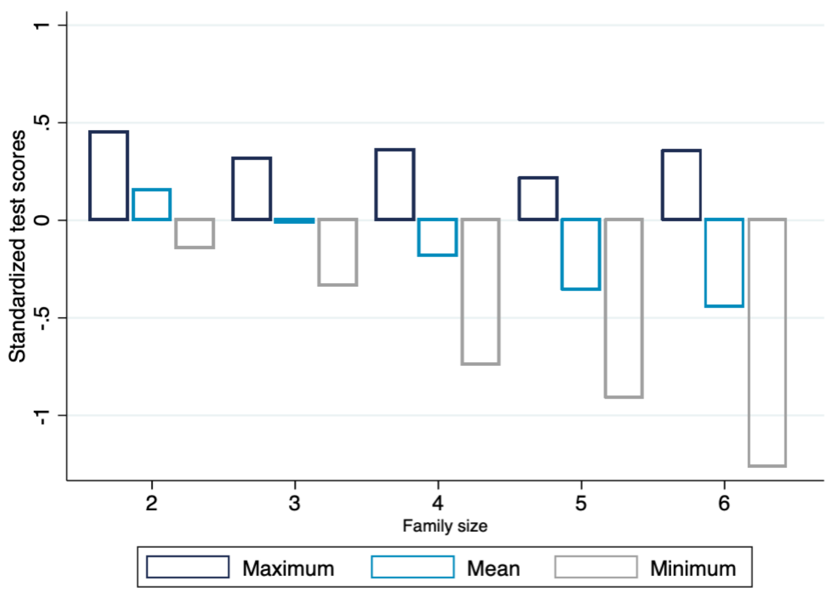
order effects, even if the data reveals a negative birth order gradient in child human capital.[10] Finally, these patterns are also evident if household size is taken as endogenous, and the model is estimated by instrumental variable techniques using twin births as an instrument.

I argue that these patters are informative about parental behaviour and are suggestive of a differential treatment of children within the family. Specifically, they are consistent with fact that parents reinforce differences in child endowments, and that reinforcement is particularly strong in larger families. In particular, the figure suggests that in resource deprived contexts parents might select one child in the family in which to focus their investments. This has large detrimental effects on the human capital of other children in the household, particularly in larger families, where per-capita resources are lower.

[10] See also Jayachandran & Pande (2017) for evidence of a negative birth order gradient in child human capital in India, and Behrman & Taubman (1986), Black, Devereux, & Salvanes (2005), Iacovou (2008), Price (2008) and Pavan (2016) for evidence in developed countries.



(A) Inequality by Family Size



(B) Human Capital Distribution by Family Size

Figure 2: Family Size and Inequality in Child Human Capital

Notes: The outcome variable is test scores. I use an age-standardized z-score, where the reference group consists of same age children children. Thus coefficients are expressed in standard deviations units. Panel A plots the within-household and between-households component of the Mean Log Deviation (MLD) measure of inequality separately by family size. By construction, the within component is zero in one-child families. Panel B plots the relationship between family size and the mean (light blue), the maximum (dark blue) and the minimum (grey) levels of human capital within the household. This figure is constructed as follows. For each family in the sample, I compute the maximum, minimum and mean levels of human capital achieved by children in that family. For each level of fertility, I then average across families. Source: India Human Development Survey (IHDS).

3 Conceptual Framework

In this section I develop a simple theoretical framework to study how parental allocations of resources across children are affected by the beliefs that parents have about the process of human capital formation and by financial resources. This model allows me to study the sources of the large intra-household inequality in child human capital outcomes documented in the previous section and the reasons why this might be affected by family size.

Preferences and constraints. For a family with n children, the utility function is specified as a Constant Elasticity of Substitution (CES) and can be expressed as:

$$U(H_1...H_n) = (a_1 H_1^\rho + a_2 H_2^\rho + ... + a_n H_n^\rho)^{\frac{1}{\rho}} \tag{1}$$

where H_i is child i human capital (e.g. adult earnings), a_i are child-specific preferences (e.g. a preference for sons over daughters) and ρ regulates parental inequality aversion in child outcomes.[11] This functional form assumption is standard in the literature on intra-household allocation of resources (Behrman, Pollak, & Taubman (1982); Behrman (1988)). The CES specification is very flexible as it allows a complete range of productivity-equity trade-offs. In particular, at one extreme when $\rho = 1$, the indifference curves become linear in children's outcomes as there are no inequality concerns. In this case parents act as return maximizing agents. The opposite case is the Rawlsian case when $\rho \to -\infty$; utility curves are L-shaped and parents act to equalize child outcomes. Finally, when $\rho = 0$ utility curves become Cobb-Douglas.

Parents choose child educational investments X_i to maximize their utility subject to two constraints. The first constraint is a budget constaint. As this is a one-period model without saving or borrowing, I write the budget constraint as:

$$y = X_1 + X_2 + ... + X_n \tag{2}$$

where y is the total educational budget, and where the price of investments is normalized to one. We can imagine a two stage budgeting process: in the first stage parents decide the total amount of resources to spend for child investments and then decide how to allocate these resources between their children. Notice that family size n does not have a direct effect on household resources y, but reduced the amount of per-capita resources available for investments y/n.

The second constraint faced by the family is a technological constraint that maps inputs into later life

[11] For the moment, I assume that n the total number of children the family has is exogenous. I discuss later how this assumption can be relaxed to endogenize the fertility choice.

outcomes. This constraint can be expressed as:

$$H_i = f(\theta_i; X_i; Z_i;) \tag{3}$$

where θ_i are child initial endowments, X_i are parental educational investments, and Z_i are other child or family characteristics (e.g. parental cognitive skills). Standard model of intra-household allocations of resources rely on strong assumptions about parental knowledge of the process of human capital accumulation. In particular, these models assume that parents have perfect information about the "true" technology of skill formation (the objective technology of skill formation in (3)). This assumption is a very strong one, and has been shown not to hold in practice. For instance, Boneva & Rauh (2018) and Attanasio, Cunha, & Jervis (2019) show that parents hold inaccurate beliefs about the productivity of different inputs entering the production function for child human capital.

Subjective beliefs. To incorporate these information frictions into the model, I introduce the *perceived* human capital production function:

$$H_i = \tilde{f}(\theta_i; X_i; Z_i) \tag{4}$$

This is allowed to differ from the actual human capital production function so that $f \neq \tilde{f}$, capturing the fact that parents have incomplete information about how inputs map into future child outcomes. Equations (3) and (4) play different roles in the model. The former describes the actual process of child development, while the latter represents subjective beliefs about the process, and is the relevant constraint used by parents to determine investment choices.[12]

Maximizing parental preferences subject to the constraints in (2) and (4) results in a investment policy function which determines parental optimal choices. This policy function depends on household resources, parental preferences, on the *perceived* human capital production function and on child endowments. Without information about the *perceived* technology, one can not derive any conclusions on parental preferences. To illustrate this point more clearly, I assume that the actual production function is Cobb-

[12] In this paper, I do not consider the issue of how parents form these beliefs and whether these can evolve over time. There are both theoretical and empirical reasons for doing so. First, the model is static so what matters to determine choices is the beliefs that parents hold at a particular point in time. Second, the data that I use are not longitudinal in nature, making them not appropriate to answer this question. A large literature in psychology suggests that individuals use heuristics to form expectation (Tversky & Kahneman (1974)). A small body of work in economics has looked at how individual form beliefs and how these evolve (Di Tella, Galiani, & Schargrodsky (2007)). The study of how the subjective expectations arise and whether and how these change over time should be the focus of future research.

Douglas in endowments and investments, and can be expressed as:

$$H_i = \theta_i^{\alpha} X_i^{\beta} \tag{5}$$

where α and β are the return to child endowments and investments. I also assume that parents know the correct functional form, but that their beliefs about the productivity of different inputs can differ from the parameters of the true production function, that is:

$$H_i = \theta_i^{a} X_i^{b} \tag{6}$$

where a and b are the *perceived* returns to endowments and investments, and these are allowed to different from *actual* returns i.e. $a \neq \alpha$ and $b \neq \beta$.[13]

Solution. Using this parametrization of the model, one can solve for the optimal level of educational investments in each child (see Appendix D.1). The optimality condition for investments in any two children in the family can be then be expressed as:

$$\log\left(\frac{X_i^*}{X_j^*}\right) = \frac{a\rho}{1-b\rho}\ \log\left(\frac{\theta_i}{\theta_j}\right) \tag{7}$$

Equation (7) shows that the interplay between parental preferences and the parameters of the *perceived* human capital production function play a key role in determining intra-household allocations. In particular, the equation shows that without information about the perceived production function it is not possible to make any statement about parental preferences using allocation data, as observed choices may be consistent with many alternative specifications of preferences and beliefs. To clearly see this point, consider a simple regression of parental allocations on child endowments. This is the "standard"

[13] While a more flexible specification for the production technology could have been used – for instance one that allows richer patterns of substitutability between inputs – previous research has found the Cobb-Douglas to be a reasonable approximation (Attanasio, Cattan, Fitzsimons, Meghir, & Rubio-Codina (2020); Attanasio, Bernal, Giannola, & Nores (2020)). Interestingly, Attanasio, Cunha, & Jervis (2019) find that this functional form can also realistically approximate how parents perceive the production function for child human capital. Moreover, modelling child human capital as a function of investments made in one period only is arguably a simplistic assumption. A vast body of research has recently highlighted the existence of different periods of child development and has documented the existence of complementaries between early and late investments (Cunha & Heckman (2007); Johnson & Jackson (2019)). These complementaries imply that the returns to human capital investments in early periods are higher when followed by investments in later periods. For tractability, I assume that investments take place only in one initial period and leave the multi-period version of the model for future research. However, the existence of dynamic complementaries in the production of human capital could provide a strong incentives for parents to reinforce endowment differences.

regression used in the literature on intra-household allocation of resources and is expressed as:

$$\log\left(\frac{X_i^*}{X_j^*}\right) = \gamma \ \log\left(\frac{\theta_i}{\theta_j}\right) = \frac{a\rho}{1-b\rho} \ \log\left(\frac{\theta_i}{\theta_j}\right) \tag{8}$$

This regression identifies a composite parameter (that I label γ), which includes both preferences and beliefs. Without imposing strong assumption on such beliefs – such that parents have perfect knowledge of the parameters of the production function – one can not learn about parental preferences. For example, finding that educational investments are not sensitive to child levels of human capital could either mean that parents care about inequality in child outcomes, or that they believe that the returns to endowments are particularly low. In both cases the estimated γ would be close to zero. Clearly, this distinction becomes crucial to the understanding of the sources of intra-household inequality, and to the design of policies that could effectively tackle it. This highlights the need to conduct a carefully designed lab-in-the-field experiment that allows to separate the role of preferences (the parameter ρ) from that of parental beliefs (the parameters a and b). In the experiment, I design a measurement instrument that allows me to elicit direct measures of a and b. I combine these beliefs estimates with experimental allocation choices to back our ρ.

Equation (7) also shows that the composite parameter γ plays a crucial role in determining the optimal investment strategy. In particular, according to equation (7):

- When $\gamma < 0$, parents invest more in child i whenever $\log\left(\frac{\theta_i}{\theta_j}\right) < 0$ i.e. whenever child i has an lower endowment compared to child j. In this case the parental investment strategy is *compensating*.
- When $\gamma > 0$, parents invest more in child i whenever $\log\left(\frac{\theta_i}{\theta_j}\right) > 0$ i.e. whenever child i has an higher endowment compared to child j. In this case parents adopt a *reinforcing* investment strategy.

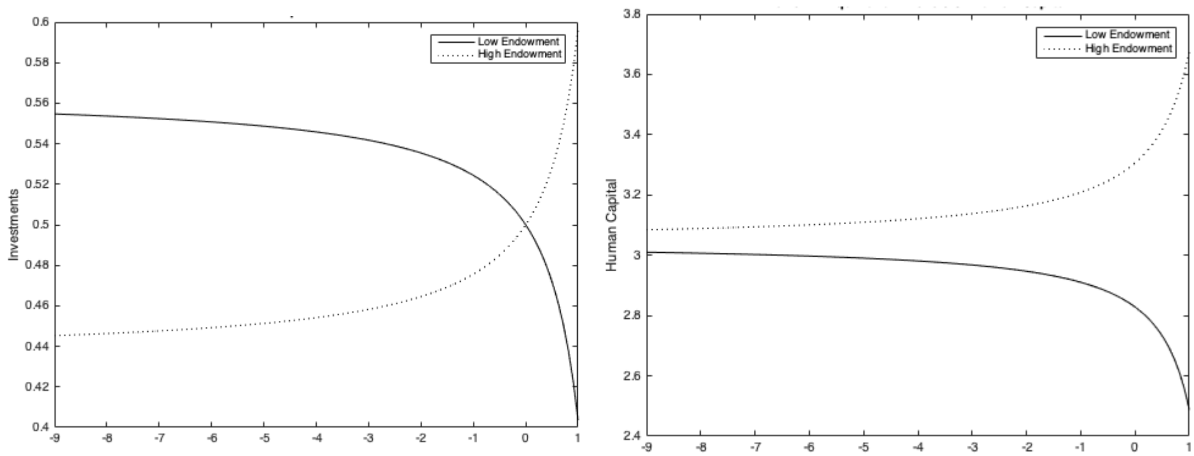
Therefore, the model predicts that as the difference between child endowments increases, the difference between investments should increase (decrease) if parents reinforce (compensate) endowment differences. Importantly, this equation also shows that a test on whether parental investments are reinforcing or compensating does provide a clean test on parental preferences for intra-household inequality, as the optimal investment strategy depends on the interplay between preferences and beliefs.

Interaction between investments and family size. So far, I have not considered how investments are affected by family size. The budget constraint shows that family size affects the amount of per capita resources available y/n, but not the level of resources y. In Appendix D.2, I show that when reinforcement is sufficiently strong, the investments made in the human capital of the highest endowment child are unaffected by family size. The intuition for this result is simple. As inequality aversion decreases, optimizing parents invest efficiently to maximize the returns from their investment. This means allocating a fixed amount of resources to high endowments children, irrespectively of family size and of the endowments of other children. Therefore, the model predicts that in larger families investments are more reinforcing because of less per-capita resources.

In scarce resource settings, parents might lack the resources to adequately investing in *all* their children, leading them to select *one* child within the family in which to focus their educational investments. This might be particularly true when inputs are not divisible (like the decision to enrol a child in secondary school), or when investing below a given threshold is not very productive. Moreover, if parents anticipate that they might not be able to follow-up on early investments with later ones, they might have an even stronger incentive to differentially invest in their children.

Intra-household inequality. *What does the optimal investment strategy imply for intra-household inequality?* I plot the optimal investment profile in panel A of Figure 3. On the x-axis there is γ and on the y-axis the optimal investments in a low endowment child (solid line) and high endowment child (dashed line). As γ goes from negative to positive, investments in the lower achiever decrease while investments in the higher-achieving child increase. In panel B of Figure 3, I plot the equilibrium levels of human capital corresponding to the investment profile on the left panel. When γ is negative parents will try to minimize the differences in their children's outcomes. This implies that the human capital distribution will be concentrated around its mean. As γ increases, the human capital of children within the household diverges as parents reinforce initial differences. This figure illustrate a simple, yet key point: intra-household inequality in outcomes is only consistent with the case when $\gamma > 0$, which itself means that parents have a low aversion for inequality in child outcomes ($\rho > 0$). This is therefore the relevant case to consider to explain intra-household inequality in child outcomes. The lab-in-the-field experiment is purposely designed to separately identify a, b and ρ and isolate the separate contribution of preferences and beliefs in explaining observed choices.

How does family size contribute to intra-household inequality? As discussed in the previous section, when investments reinforce child endowments the level of resources invested in the highest achieving child will be unaffected by family size. The implications of this investment behaviour – coupled with the existence of decreasing returns to investments – is that as family size increases there is a shallow gradient



(A) Investments

(B) Human capital

Figure 3: Preferences, Investments and the Human Capital Distribution

Notes: Panel A plots the equilibrium level of investment in child i and child j as a function of γ. Panel B the corresponding levels of human capital as a function of γ.

in maximum child quality and a steep drop in the quality of the lowest achieving child.[14] This implies that the level of intra-household inequality will increase with family size. In particular, low endowment children are especially penalized by increases in family size both because by having more siblings they face more competition over resources, and because they are likely to fare poorly compared to their siblings when competing with them.

3.1 Discussion of the model

I this section, I discuss some of the most relevant features and assumptions of the model and how some of these assumptions can be relaxed. I conclude with a discussion of the model's implications for the Quantity-Quality trade-off.

Gender preferences. By including weights to child human capital in the parental utility function (1), the model is general enough to incorporate social norms such as gender preferences or other details that are important in specific contexts. For instance, a literature suggests that in the Indian context parents have a preference for sons over daughters (Gupta (1987); Jayachandran (2017)). This gender preference is particularly strong in for some parts of India – particularly in the North-West – and significantly less pronounced in other states (Jayachandran & Pande (2017); Yadav, Anand, Singh, & Jungari (2020)).

[14]Decreasing marginal product of investments means that a reduction in investments will have a much larger impact on child human capital when it happens at a low baseline level of investments, that when it happens at a high baseline level. Appendix D.2 and Appendix Figure D.1 discuss in greater detail the intuition behind this result.

In solving the model I set these utility weight equal to each other. This is because I do not find strong evidence of a gender preference in the reality of my setting. In particular, there is no evidence of a skewed sex ratio in the sample (see Table 1). This finding is consistent with the fact that the state of Orissa (where the data used in this paper come from) has one of the less skewed sex ratios in the country (see Appendix Figure A.2).[15] Moreover, previous work demonstrates a non-significant discrimination against girls in Orissa in terms of post-natal investments (IIPS (2001); IIPS (2008); Padhi (2001)).[16] I discuss gender preferences in greater details when I present the results from the lab-in-the-field experiment.

Child endowments. One important feature of the model is child birth endowment. This paragraph discusses what these endowments are and whether they are observed by the parents.

Endowments at birth encompass a variety of different characteristics that include both health and cognitive ability. Several recent studies that rely on measures of child health at birth to proxy for endowments often have health in mind as the key dimension. Empirically this is operationalised using birth weight as a measure of human capital at birth (see for example Datar, Kilburn, & Loughran (2010) and Hsin (2012)). Theoretically this assumption is not needed and is often made for tractability, given that obtaining information on child cognitive endowments can be even more challenging. One exception is Adhvaryu & Nyshadham (2016) that considers child cognitive abilities by exploiting a large-scale iodine supplementation program in Tanzania. Therefore, in practice endowments at birth might comprise a bundle of health and cognitive skills. As illustrated by the model, what matters to study parental behaviour is that these endowments affect the return to investing in a child and are thus relevant to determine child long run human capital outcomes.

This discussion leads to the question of whether parents can observe endowments. While this assumption is implicitly made by most models relating endowments to subsequent parental behaviour, there is no explicit discussion of whether it holds in practice. A large medical literature suggest that parents are indeed able to recognise their child health endowments from very early ages. For instance, Channon (2011) and Chirande et al. (2015) indicate that mother's perception of their child's size is a good proxy for actual birth weight. On the other hand, recent evidence from the economics literature suggests that

[15] Chao, Guilmoto, KC, & Ombao (2020) predict that by 2030 the sex ratio in Orissa (male to female) will be the third lowest in the country (following Kerala and Chhattisgarh) and will be of 105 males per 100 females, which corresponds to the natural sex ratio at birth WHO (2019).

[16] In terms of educational investments, in urban areas school attendance is the same for boys and girls in the age groups 6-10 years and 15-17 years, and slightly higher for girls than boys in the age group 11-14 years (81% of girls compared with 78% of boys). Similarly, in terms of health investments and outcomes, the infant and under-five mortality rates are 23-26 percent higher for boys than for girls. Among surviving children, girls and boys are about equally likely to be undernourished. Girls are also more likely than boys to be fully vaccinated (55% of girls, compared with 49% of boys). Table A.5 further shows that compared to the rest of the country, girls in urban Orissa are less likely to belong to larger families.

sometime parents might have inaccurate perceptions about their children's cognitive ability, causing the mis-allocation of education investments (Dizon-Ross (2019)).[17] Importantly, the theoretical framework can be easily extended to allow for this possibility. Specifically, by replacing *actual* endowments in the perceived human capital production function with *perceived* endowments one can derive similar implications for parental investment behaviour. What will matter now to determine the allocation of resource across siblings is *perceived* child endowments. Moreover, the empirical strategy that I use – that relies on the use of hypothetical scenarios – is robust to the possibility that parents might have inaccurate beliefs about their children's endowments.

Fertility choices. One assumption made in the model is that parents choose child educational investments conditional on an exogenously given family size n. The theoretical framework can be easily extended to allow parents to choose fertility endogenous. To do so, assume that parents first decide sequentially on the number of children they have. Once the fertility spell is concluded, they decide how to allocate educational investments. The model can be solved backwards, and implies an stopping problem: in each period parents compare the utility from having n children with the expected utility of having $n+1$ children. They will stop when the former is greater than the latter (see Appendix D.3 for a formal derivation of the optimal stopping rule). Fertility choices depend on parental preferences for intra-household inequality (the parameter ρ). In particular, the model implies an endogenous fertility response to child endowments so that parents are more likely to increase fertility after giving birth to a low endowment child.[18] Importantly, the optimal allocation rule is not affected by the fertility decision: The results derived in the previous section are still valid when allowing for endogenous fertility. If anything, those results are reinforced by the fact that, because of the optimal stopping rule, children born with low initial conditions are more likely to belong to larger families, resulting in them having more siblings and thus facing more competition over limited resources.

The Quantity-Quality trade-off. When parents reinforce endowments differences, the model implies the existence of a negative relation between family size and average child quality (the Quantity-Quality trade off), even if the maximum level of human capital stays constant as family size increases. This sug-

[17]Interestingly, these results are at odds with a psychology literature suggesting that mothers are able to assess and react to signals of cognition in their infant children from as early as a few days after birth (Brazelton (1984); Brazelton (2011); Bullowa (1979); Susman-Stillman, Kalkoske, Egeland, & Waldman (1996)).

[18]I test and find empirical support for this model's prediction in Appendix D.5. Interestingly, this prediction is also consistent with the demographic transition literature, which shows that reductions in child mortality are associated with a decline in fertility (Soares (2005)), and with a public health literature documenting that improvements is health at birth are associated with reductions in maternal fertility (Canning & Schultz (2012)).

gests that when parents target their investments to the endowment of their children, an increase in family size can differentially affect children living in the same family. Because of allocation of resources that take place within the household, changes in family size will have asymmetric effects on different children, so that average treatment effects might be misleading. In particular, while high achieving children are not affected by variations in family size, the human capital of low achieving children sharply declines as family size increases. This heterogeneous effect of family size on child outcomes could potentially explain why the empirical findings in the Quantity-Quality literature are mixed, with some studies finding evidence in favour of a trade-off (Rosenzweig & Wolpin (1980); Hanushek (1992); Rosenzweig & Zhang (2009); Mogstad & Wiswall (2016); Bhalotra & Clarke (2018)), while other against (Black, Devereux, & Salvanes (2005); Angrist, Lavy, & Schlosser (2010); Cáceres-Delpiano (2006)). What the model suggests is that family size *per se* might have little effect on child human capital, what matters for child outcomes is the effect that family size has on per-capita resources, combined with parental investment decisions.

4 Lab-in-the-field Experiment

The conceptual framework, highlights the separate role that parental preferences, beliefs and financial resources have to determine household choices and determine intra-household inequality in child outcomes. It also illustrates the challenges that observational data pose for the identification of key parameters and mechanisms of interest. The reason for this challenge is a twofold identification issue. First, realized choices may be consistent with many alternative specifications of preferences and beliefs (Manski (2004)). Second, credit constraints might prevent parents from selecting their preferred choices, breaking the direct connection between observed outcomes and parental preferences (Baland & Robinson (2000)).

To overcome these identification challenges and understand the drivers of household behaviour, I design and implement a lab-in-the-field experiment with parents of primary school children in India. In the experiment, I use a novel survey methodology based on hypothetical scenarios that is closely guided by the theoretical model. This allows me to identify parental beliefs about the human capital production function, and in particular about the returns to endowments, investment, and their complementarity or substitutability. I then use hypothetical scenarios, to collect parents stated investment choices. Combining the answers in the second stage with the elicited beliefs from the first stage, I identify parental preferences for intra-household inequality. Furthermore, scenarios vary in terms of resources available to the family. This allows to understand whether financial resources are important in determining parental allocative decisions. Next, I describe in detail the measurement tools, the experimental procedures and how I combine experimental measures to identify structural parameters of interest.

4.1 Parental Beliefs

Measurement tool. To elicit parental beliefs about the human capital production function, I design a novel measurement strategy. I build on the work of Cunha, Elo, & Culhane (2013), Boneva & Rauh (2018) and Attanasio, Boneva, & Rauh (2019), and use hypothetical scenarios. The use of hypothetical scenarios has the advantage that one can vary one input at the time while holding *all* other inputs fixed, thus identifying the *perceived* productivity of different inputs. I construct the measurement tool adapting it to the research question that I want to answer. To this aim, I presented each respondent with a series of hypothetical stories (or scenarios) about a representative family. Guided by the theoretical framework, I focus on the role of perceived returns to child endowments and parental investments, and on their perceived complementarity or substitutability, as these are the key parameters that matter for the allocative decision. In each scenario, I varied exogenously one input and asked the respondent to report what they believed the future earnings of the child would be at age 30 (this corresponds to child human capital H_i in the theoretical framework). As a robustness check, I also asked parents to state what they believed the educational attainment of the child would be under each hypothetical scenario.

To elicit subjective expectations using hypothetical scenarios one can either ask respondents about their own children or about hypothetical children. Advantages and disadvantages of each method are discussed in Delavande (2014). I decided to ask parents about hypothetical children rather than their own, because this allowed to vary one input at the time while holding other characteristics of the hypothetical children constant. One particularly important input in this context is child initial conditions. Exogenous variation in this input would clearly not have been possible if I asked respondent about their own child.

The experimental procedure worked as follows. Surveyors asked respondents to think about a representative family that lives in a neighbourhood like their own. The family has *two* children who attend the same school and are identical in many respects. However, while the first child (Child H) has an high initial skill level, the second child (Child L) has a low initial skill level (this corresponds to child endowments in the model). Specifically, respondents were told that the hypothetical family had two healthy children who attended the same school. But while Child H was described as being *among the top three students in his/her class*, Child L was described as being *among the bottom three students in his/her class.* Scenarios then varied in term of the amount of monetary investment made by the family in each child. After presenting the scenario, surveyors asked respondents to report what they believed the outcome would be for each child.[19] The respondent's answer was recorded, and the experiment moved to the next scenario. To insure understanding, all scenarios were presented to the respondent with the help of a visual aid that sketched the main features (see Figure A.3 for an example of the visual aids used in the field).

Presenting respondents with an hypothetical family with two children rather than two distinct families with one child each has the advantage of holding fixed many of the unobserved factors that might matter for child outcomes and that vary between families (e.g. parental income and the family environment). Finally, to understand whether parents perceived these returns to differ by gender, I further randomized the gender of one of the two children across respondents so that one group saw two boys, while the other group saw one boy and one girl.

Identifying the perceived production function. Comparing parental responses across scenarios and between children one can identify: (i) the perceived returns to monetary investments, (ii) the perceived returns to endowments, and (iii) the perceived complementarity or substitutability between these two inputs.[20] For example, comparing responses across scenarios where investments are high to the corresponding scenarios where investments are low one can indentify the perceived returns to this input.

To characterise the perceived production function of child human capital, I estimate the following empirical specification using ordinary least squares:

$$y_{i,j,k} = \alpha_0 + \alpha_1 \theta_{j,k} + \alpha_2 I_{j,k} + \alpha_3 \theta_{j,k} \times I_{j,k} + \gamma_i + u_{i,j,k} \tag{9}$$

where i indicates the respondent, j the scenario and k indicates one of the two children, $y_{i,j,k}$ are expected (log) earnings, $\theta_{j,k}$ is a dummy equal to one if the initial skill level of child k is high, $I_{j,k}$ is a dummy equal to one if investments in child k are high, and γ_i are respondent fixed effects. The coefficients α_1 and α_2 identify, respectively, perceived returns about endowments and investments, while the coefficient α_3 identifies the perceived complementarity or substitutability between these two inputs. If parents perceive initial endowments and investments to be complements we would expect $\alpha_3 > 0$, while substitutability implies the opposite.

[19] Appendix F presents the exact wording of some relevant questions used in the survey.

[20] The Cobb-Douglas specification used in the conceptual framework implicitly assumes that the two inputs are complements. Importantly parents might believe this is the case or not. For this reason it is important to elicit parents' perceptions about this feature of the human capital production function.

4.2 Investment Choices

Measurement tool. Having characterised the features of the perceived human capital production function, in the second round of the experiment I collect parental stated investment choices. The measurement tool used in this stage is similar to the one used to elicit parental beliefs: As in the case of beliefs, respondents are presented with a series of hypothetical scenarios. But in this stage of the experiment, instead of asking respondents to report what they believe the outcome of the child would be, I ask them to select their favourite allocation choice.[21]

Respondents are presented with a representative family who makes a decision about how to distribute educational resources across their *two* children. Guided by the theoretical model, across scenario I exogenously varied: (i) the endowments of the two children, and (ii) the total amount of resources the family can spend on their children's education. In particular, the model predicts that as the difference between childrens' endowments increases, the difference between investments should increase (decrease) if parents reinforce (compensate). Importantly for identification, I therefore varied the *difference* in endowments existing between the two children across scenarios. As in the case of beliefs while the higher achiever was described as being *among the top three students in his/her class*, the lower achiever was described either as being *among the bottom three students in his/her class* or as *an average student in his/her class.* After presenting each hypothetical scenario, respondents are asked how they would allocate resources. Specifically, parents are asked to distribute some tokens to reflect their choices.[22] Surveyors recorded the respondent's answer, collected the tokens and moved on to the next scenario. All hypothetical scenarios were presented to the respondent with the help of visual aids similar to those used to elicit parental beliefs. To ensure understanding, two practice scenarios in which parents had to allocate tokens according to a well defined allocation were presented at the beginning of the experiment. If parents could not correctly identify the practice allocations, surveyors continued explaining how to do it.

Comparing parental allocations across scenarios, I can thus test whether investment reinforce or compensate endowment differences. To understand whether investment choices are affected by household resources, I then compare responses in scenarios in which resources are high with the corresponding choices in scenarios in which resources are low.

I decided to vary the resources available to the hypothetical family rather than the number of children in the family to avoid respondents' confusion and for consistency with the scenarios used to elicit parental

[21]This approach, which relates to "contingent valuation" methods used in the field of marketing research, has been recently used in economics to study preferences for workplace attributes, university choices, marriage markets, saving behaviour and labour force participation (Mas & Pallais (2017); Wiswall & Zafar (2018); Delavande & Zafar (2019); Adams-Prassl & Andrew (2020); Ameriks, Briggs, Caplin, Shapiro, & Tonetti (2020); Ameriks, Briggs, Caplin, Lee, et al. (2020)).

[22]The exact wording of some relevant questions used in the survey is presented in Appendix F.

beliefs. Moreover, as discussed later, most families in the sample have two children, implying that the hypothetical scenarios are particularly relevant and realistic for them. Importantly, the model shows that the only way family size affects human capital investments is through per-capita resources.

To characterize parental investment strategies, I estimate variants of the following empirical specification using ordinary least squares:

$$s_{i,j} = \beta_0 + \beta_1 diff_j + \gamma_i + u_{i,j} \tag{10}$$

where i indicates the respondent and j the scenario, $s_{i,j}$ is the share of total resources allocated to the high endowment child, and $diff_j$ is a dummy variable that is equal to 1 if in scenario j the difference between the endowments of the two children is high and zero otherwise.[23] The sign of β_1 pins down whether parental responses are reinforcing ($\beta_1 > 0$) or compensating ($\beta_1 < 0$). To test whether resources matters to explain intra-household allocations, and in particular whether competition is stronger when resources are lower, I expand equation (10) and estimate:

$$s_{i,j} = \beta_0 + \beta_1 diff_j + \beta_2 res_j + \beta_3 diff_j \times res_j + \gamma_i + u_{i,j} \tag{11}$$

where res_j is a dummy variable that takes value 1 if in scenario j resources are high and zero otherwise. The coefficient β_3 captures whether competition is stronger when resources are lower ($\beta_3 < 0$).

4.3 Combining Measures to Identify Parental Preferences

While estimates of equations (10) and (11) are informative of whether parents reinforce or compensate endowments differences, without further assumptions on parental beliefs we are not able to say anything about preferences for intra-household inequality. This point can be easily illustrated looking again at equation (8), which is reported below for convenience.

$$\log\left(\frac{X_i^*}{X_j^*}\right) = \gamma \ \log\left(\frac{\theta_i}{\theta_j}\right) = \frac{a\rho}{1-b\rho} \ \log\left(\frac{\theta_i}{\theta_j}\right)$$

A simple regression of parental allocations on child endowments identifies a composite parameter that includes both preferences and beliefs. Without imposing strong assumption on such beliefs – such that parents have perfect knowledge of the parameters of the production function – one can not infer

[23]The outcome variable is expressed in terms of resource share rather than in terms of differences in order to allow comparability between scenarios in which resources are high and scenarios in which they are low.

much about preferences.[24] For example, if one were to find that parental allocations are insensitive to endowments, it might either be that parents have a low concern for intra-household inequality and equally distribute resources between children (ρ is close to 0), or it could be that parents perceive the returns to endowments to be particularly low (a is close to 0). In both cases the estimated γ would be close to zero. Clearly, this distinction becomes crucial to the understanding of the sources of intra-household inequality, and to the design of policies that could effectively tackle it.

Combining the structure of the model with experimental data on beliefs and choices, I identify parental preferences for intra-household inequality using reduced form regressions. The intuition for the identification result is simple. As discussed in section 4.1, regressing expected child outcomes on investments and endowments I identifies the parameters of the perceived production function (a and b). Moreover, parental stated choices in the intra-household allocation module can be used to estimate the reduced form parameter γ. Armed with these estimates, one can identify the structural parameter relating to parental preferences for intra-household inequality as follows:

$$\rho = \frac{1}{a} \times \left[\frac{1}{\gamma} + \frac{b}{a}\right]^{-1} \tag{12}$$

A consistent estimator for ρ can then be obtained by replacing the parameters in (12) with the corresponding ordinary least squares estimates from equations (9) and (10). Standard errors and confidence intervals can be obtained using bootstrap methods.[25]

Importantly, the identification strategy not only accounts for to the possibility that perceived returns might differ from actual one, but it is also robust to the fact that parents might hold inaccurate beliefs about their children's endowments (Dizon-Ross (2019)). As I have control over *all* the characteristics of the hypothetical scenario, I can precisely describe child endowments to the respondent, thus avoiding the issues related to the fact that objective measures of child endowments (which can, not without challenges, be identified in the data) might not accurately reflect parental beliefs about these endowments (which are usually not observed).

[24] Even if one is willing to make these assumptions on parental beliefs, then the parameters of the *objective* production function should still be estimated. The two key challenges one faces in obtaining consistent estimates of these parameters are the fact that some of the argument entering the production function are chosen by parents and are therefore likely to be endogenous. Moreover some of the relevant inputs might only be observed with measurement error. Cunha, Heckman, & Schennach (2010), Attanasio, Meghir, Nix, & Salvati (2017), Attanasio, Bernal, Giannola, & Nores (2020), Attanasio, Cattan, Fitzsimons, Meghir, & Rubio-Codina (2020) and Attanasio, Meghir, & Nix (2020) describe how to deal with these issues in order to obtain consistent estimates of the parameters of the production function.

[25] Given consistency of the OLS estimator, using the continuous mapping theorem and Slutsky theorem one can prove consistency of the estimator for ρ.

	Mean	S.D
A. Household characteristics		
Primary caregiver has no formal education	0.508	0.500
Primary caregiver age	27.933	6.216
Household size	6.512	3.285
Number of children	2.296	0.930
Household owns dwelling	0.712	0.453
Number of rooms	2.766	2.278
Household is attached to sewage system	0.312	0.464
Yearly food expenditure†	71.463	49.788
B. Children's characteristics		
Child age	7.438	3.510
Child is male	0.482	0.500
Yearly educational expenditure per child†	6.662	9.555
C. Household members' characterstics		
Household member age	26.129	18.538
Household member is male	0.481	0.500
Total number of households	504	
Total number of children	1196	
Total number of individuals	3282	

Notes: This table presents the summary statistics for the sample. Panel A reports the household statistics, Panel B the statistics for children and Panel C the statistics for all household members. † indicates expenditure in thousands of INR. Educational expenditures include school tuition, money spent on purchasing textbooks and stationery, and hiring private tutors. The exchange rate was 71.43 INR : 1 USD at the time of the study.

Table 1: Summary Statistics

Stated and revealed preferences. One natural question is whether preferences recovered from data on hypothetical choices relate to observed behaviour. To address this question, I also collect data on actual investments made by parents in the form of child specific educational expenditure. I investigate whether parents that are predicted to be less inequality averse in the intra-household allocation module systematically make more unequal choices when it comes to distribute actual resources. Evidence in favour of this relation would add credibility to the research design, and to the use of hypothetical scenarios to identify structural parameters of interest.

5 Data and Descriptive Statistics

The experimental sample consists of around 500 households in the urban slums of Cuttack, Odisha, India. The data collection was part of a long run follow-up of a cluster randomised controlled trial of a psychosocial stimulation intervention for disadvantage children.[26,27] In 2013 a random sample of poor women with young children (aged 10 to 20 months then) was identified through a door-to-door census. In 2019, we aimed at re-interviewing all households in the original sample. To increase statistical power (for the purpose of this study), in larger slums one or two neighbours of randomly selected households from the original experimental sample were also interviewed. To take part to this study, the neighbour household had to have at least one child of the same age as "target" children from the original study (i.e. between 6 and 8 years old at the time of this study). Survey respondents were children's female primary caregivers, who were almost always their mothers.[28] The lab-in-the-field experiment took place in respondents' homes, during the caregivers' endline survey and, whenever possible, in a quiet and private environment.

Table 1 reports the summary statistics for the sample. It shows that this is an economically and socially disadvantaged population: only 50 percent of children's primary caregivers have any formal education, and just over 30 percent of household are attached to the sewage system. Families in the sample are relatively young as shown by the average age of the respondent of 28 years old. The average number of children in the family is 2.3, and their average age is 7.5. Therefore for most parents distributing resources between *two* children is potentially very relevant and realistic as this is the *actual* choice they face everyday. The table also shows that the percentage of sons among children is 48 percent. Therefore, as also discussed in section 3, there is no evidence of a strong son preference in the context of this study, and if anything the sex ratio is slightly skewed towards females (this is also true if we consider all household members and not children specifically).[29] On average, parents spend INR 6662 (93 USD) a year on each of their children's education.

6 Results

This section is organized as follows. Section 6.1 presents the results on parental subjective beliefs about the human capital production function. The results on stated choices and what these imply for parental preferences for intra-household inequality are presented in section 6.2. In section 6.3 I relate the experimental measure of preferences to actual parental educational investments made by parents in the

[26]See Andrew et al. (2019) for details of the intervention and its short term impacts on child human capital.

[27]Appendix Tables A.1 and A.2 show that the treatment effects on parental preferences and beliefs are negligible. This is consistent with the results from the first follow-up, showing that there were no improvements in maternal knowledge of child development (Andrew et al. (2019)). I thus ignore the treatment allocation and report results pooling the treatment and control groups together in the following sections.

[28]Written consent was obtained from all caregivers before proceeding to the survey and experiments.

[29]In 2019, the national sex ratio was 108 boys per 100 girls (United Nations (2019)). The "sex ratio at birth" is considered to be around 105 boys per 100 girls.

sample.

6.1 Beliefs

I present the estimates of equation (9) in Table 2. I start by regressing perceived (log) earnings on a dummy for high endowment and a dummy for high investment in column 1. I subsequently control for child gender and for the interaction between endowment and investment (columns 2 and 3). In column 4, I also include respondent fixed effects. Finally, in column 5 I control for child educational attainment (as expected by parents).[30]

A few interesting findings emerge. First, parents perceive the returns to initial conditions to be particularly high: high endowments are associated with an increase in earnings of between 70 percent to 80 percent. At the sample mean of expected earnings this corresponds to an increase of roughly INR 13,000 to 14,000. Interestingly, almost 50 percent of the effect of endowment is mediated by higher educational attainment (column 5). In particular, as show in Table A.3, parents believe that children with high initial skills will achieve, on average, two years more of schooling compare to children with a low initial skills level. In turn, one year more of schooling is expected to increase earnings by 16.9 percent (column 5 of Table 2). Second, column 2 shows that high investment is perceived to increase earning by 24.6 percent. Third, the results in column 3 imply that endowment and investment are complements: parents perceive the returns to investments to be 10.3 percent higher for a high endowment child compared to a low endowment child. The existence of perceived complementaries in the production function for child human capital provides a potential rationale for parents to invest more in children with higher baseline endowments.

Benchmarking perceived returns. Table 2 reports the coefficients associated with a binary increase in the relevant input (i.e. a change from a *low* level of the input to an *high* level). As such, they can not be easily interpreted or compared. To ease interpretation and comparability, I convert these coefficients in terms of a one-standard-deviation increase in the relevant input. This exercise reveals that parents perceive a one-standard-deviation increase in endowments to increase earnings by 15 percent. Similarly, a one-standard-deviation increase in investments is expected to boost earnings by 28 percent. To put these figures into perspective, I contrast them with expected gender-gap in earnings. In my sample, parents expect boys to earn on average 16 percent more than girls at age 30. Interestingly this figure is quite close to the actual gender-gap in urban workers' earnings of 22 percent (ILO (2018)). Interestingly, I also find

[30] Results for educational attainment follow a quantitative similar pattern and are presented in Table A.3.

Outcome variable: Log earnings at age 30	(1)	(2)	(3)	(4)	(5)
High endowment	0.768*	0.848*	0.796*	0.717*	0.371*
	(0.021)	(0.030)	(0.031)	(0.022)	(0.028)
High investment	0.246*	0.246*	0.194*	0.194*	0.152*
	(0.009)	(0.009)	(0.011)	(0.011)	(0.010)
Boy		0.159*	0.159*	-	-
		(0.041)	(0.041)		
High endowment x High investment			0.103*	0.103*	0.102*
			(0.013)	(0.013)	(0.013)
Belief about child education					0.169*
					(0.012)
Family fixed effects				✓	✓
Observations	7920	7920	7920	7920	7920

Notes: The outcome variable is log-earnings of the child at age 30 as perceived by the respondent. Columns 1 to 3 display the OLS results. Columns 4 to 5 further include family fixed effects. Robust standard error clustered at the family level are reported in brackets. *High endowment* is a dummy variable that takes value 1 if in scenario j the child has an high initial skill level, *High investment* is a dummy variable that takes value one if in scenario j the level of investments is high, and *Boy* is a dummy variable equal to one if the child is a boy. *Belief about child education* is the educational attainment respondents' believe the child will achieve in scenario j.
* denotes 5% significance.

Table 2: Perceived Human Capital Production Function

that while parents believe that girls on average will command less resources than boys as adults, they do not perceive the returns to endowments or investments to substantially differ by gender (see Appendix Table A.4). These findings imply that parents do not perceive the technology of skills formation to differ by gender, but are suggestive of the fact that parents incorporate the prevailing social norms in their communities reflecting the differential treatment of women and men in the labour market.

Beliefs heterogeneity. The estimates in Table 2 represent *average* beliefs about the returns to different inputs. However these mask a substantial degree of heterogeneity. To construct an individual measure of perceived return to monetary investment, I follow Attanasio, Boneva, & Rauh (2019) and compute the difference between respondent's expected earnings in the scenarios in which investments are high and the scenarios in which investments are low and take an average across scenarios (I do this separately for high and low endowment children). Panel A of Figure A.4 plot the empirical cumulative distributions of individual perceived returns to investments (separately for low and high endowment children). The figure reveals a substantial degree of heterogeneity in perceived returns and that, consistently with the findings form Table 2, returns are perceived to be higher for children with higher endowments. By comparing expected earning across the two children while holding the level of investment fixed, I also compute the

Outcome variable: share of resource to child H	(1)	(2)	(3)	(4)
Difference in endowments	0.078*	0.078*	0.102*	0.102*
	(0.005)	(0.006)	(0.008)	(0.009)
High resources			0.028*	0.028*
			(0.007)	(0.008)
Difference in endowments × High resources			-0.048*	-0.048*
			(0.008)	(0.009)
Boy	-0.001		-0.002	-
	(0.008)		(0.008)	
Family fixed effects		✓		✓
Observations	1980	1980	1980	1980

Notes: The outcome variable is the share of total resources invested in child H. This variable ranges from 0 to 1. The average of this variable is 0.52. Columns 1 and 3 display the OLS results, while columns 3 and 4 further includes family fixed effects. Robust standard error clustered at the family level are reported in brackets. *Difference in endowments* is a dummy variable that takes value 1 if in scenario j the difference between the two children's endowments is large and zero otherwise, *High resources* is a dummy variable that takes value one if in scenario j the level of resources is large and zero otherwise and *Boy* is a dummy variable that takes value one if the respondent was randomized in seeing two boys and zero if the respondent was randomized in seeing one boy and one girl.
* denotes 5% significance.

Table 3: Intra-household Allocation of Resources

individual perceived returns to initial conditions. The distribution of these perceived returns is shown in panel B of Figure A.4, and also shows substantial heterogeneity in beliefs.

6.2 Investment Choices and Preferences

Table 3 reports the estimates of equations (10) and (11). I start by running the model without respondent fixed effects (columns 1 and 3) and then add them in (columns 2 and 4). The coefficient in column 1 shows that as the difference between child initial conditions increases parents reallocate resources within the family and devote a significantly larger share of resources to the child with the higher initial condition. The point estimate implies a 7.8 percentage points increase in resources allocated to child H, which at the "average allocation" corresponds to a 15 percent increase. The positive coefficient therefore implies that parental investment strategies are reinforcing.

Interestingly, I do not find evidence that parental choices depend on the gender of the child. I also tried estimating equations (10) and (11) separately for the two different subgroups (defined based on the gender of the two children) and found very similar results. Although the previous literature does not always find evidence of differential treatment of boys and girls, some work on India has shown that boys are breastfed longer (Jayachandran & Kuziemko (2011)) and receive more childcare time early in life

(Barcellos, Carvalho, & Lleras-Muney (2014)). To interpret our results, however, one has to keep in mind that the input being allocated here is educational *expenditure*. Consistently with the findings in Table 3, previous research has found no evidence of parents spending differently on boys and girls (Deaton (1989) and Deaton (1997)). Moreover, in interpreting these results one has to consider that, as discussed earlier, in urban Orissa there is little evidence of girls receiving less human capital investments compared to boys, nor there is evidence in the sample of a skewed sex-ratio, suggesting that son preference be less important in the context of this study (see Table 1).

It might then seem odd that parents equally allocate investments between boys and girls, despite them perceiving girls to be able to command less resources as adults (as shown in Table 2). One potential reasons that could explain this result might have to do with the fact that, when deciding on their daughter's schooling, parents also consider the marriage market returns to girls' education (in addition to the labour market returns). Indeed, recent evidence suggests that a key motivation for investing in girls' education is a substantial perceived marriage market return to schooling (Adams-Prassl & Andrew (2020); Ashraf, Bau, Nunn, & Voena (2020)).[31,32]

The results in column 3 show that reinforcement is stronger when resources are lower. This is captured by the negative and statistically significant coefficient on the interaction between children's endowments difference and the high resources dummy variable. Specifically, when resources are low the share allocated to the high endowment child is 10.2 percentage points higher in scenarios where the endowment difference is large compare to when it is small. This difference is halved when resources are high. This result highlights the important role that financial constraints have in determining investments in child human capital. Importantly, the finding implies that resources are key to explain investment behaviour within the household, and complements previous research showing that resources are an important determinant of investment differences between households (Attanasio & Kaufmann (2009); Lochner & Monge-Naranjo (2012)). Therefore, it seems likely that relaxing credit constraints can contribute to close investments gaps across children, potentially also resulting in lower inequality in outcomes. This might be particularly relevant for larger families, where per-capita resource are lower and competition over scare resources is stronger.

[31] This interpretation is also consistent with the results in Table A.3 which shows that parents do not expect girls and boys' educational attainment to differ substantially.

[32] It is also important to remember that participants to the experiment were *female* primary caregivers, and allocations made by women may differ compared to those made by men or by couples (Armand, Attanasio, Carneiro, & Lechene (2016)), particularly in terms of child gender (Ringdal & Hoem Sjursen (2020)). A related literature highlights a relationship between female control of resources and improved child outcomes (see Haddad & Hoddinott (1994), Duflo (2003), Qian (2008)).

Preferences. As discussed earlier, the coefficient on the difference between children's endowments directly relates to the composite parameter in equation (8). This parameter comprises both parental preferences for inequality and their perceptions about the production function. Using the estimates of parental perceptions about the human capital production function from the previous section, one can identify parental preferences for intra-household inequality. I find that the estimated ρ is positive and statistically significant at the 95% significance level, implying that parental do not care about equalizing their children's outcomes: the point estimate is 0.449, with an associated standard error of 0.041.

Similarly to the case of beliefs, I also find a large degree of heterogeneity in parental preferences for intra-household inequality. I plot the empirical cumulative distribution function of individual preferences in Figure A.5. Interestingly, all families in the sample are predicted to be not averse to inequality in child outcomes, but some families are significantly less inequality averse than others (i.e. they have an higher value of ρ). I use this heterogeneity to classify families as *low* and *high ρ types* by splitting the sample at the median value of ρ as indicated by the vertical line in Figure A.5.[33]

6.3 Stated and Revealed Preferences

One last key question that I address is the relevance of the results outside the experimental environment and, in particular, whether elicited preferences are reflective of what respondents would do outside of the experimental setting, i.e. that experimentally elicited preferences relate to *actual* household behaviour. To answer this question, I exploit rich information on current investment behaviour, and relate child-specific investments to child endowments. To measure children's endowments, I rely on the following survey question:

> "*Using the scale, can you please show me how intelligent do you think "child" is? In general, not only in school. If you think that "child"'s intelligence is extremely good you should score 10, while if you think that "child"'s intelligence is very poor you should score 0.*"

Notice that what this questions captures is a belief held by parents about their children's ability, which might or might not be accurate. Importantly, what matters to understand intra-household allocations is whether these beliefs (more precisely the difference in beliefs between two children) can explain parental investments.

The results are presented in Table 4. I start by running the "standard" regression in the literature and regress the difference in educational expenditure between two children (conditional on being enrolled in school) on the difference between their endowments, controlling for other observable characteristics

[33] To construct this figure, I use individual perceived returns from the previous section rather than average beliefs.

Outcome variable: difference in expenditure	All (1)	Low ρ (2)	High ρ (3)
Difference in endowments	378.044*	221.317	470.211*
	(88.320)	(132.537)	(117.972)
Mean expenditure	6662	6662	6662
Observations	1100	552	548

Notes: The outcome variable is the difference in investment between two children, as measured by educational expenditure in Rupees. Column 1 report the results in the full sample, while columns 2 and 3 report separate results for two separate sub-samples as defined by their inequality aversion (low ρ means higher inequality aversion). These two groups are defined based on whether the estimated ρ falls above or below the sample median. Robust standard error clustered at the family level are reported in brackets. Controls include child age and gender. $^{*}p < 0.05$

Table 4: Actual Parental Investments

including child age and gender. The results of this regression are presented in column 1 and suggest a positive and significant correlation between child endowments and parental investments. In particular, the point estimate implies that a 10 percent increase in the difference between children's endowments is associated with an increase in educational expenditure gap of INR 378. This corresponds to a 5.6 percent of total yearly educational expenditure. In Appendix Table A.6, I show that higher endowment children are also more likely to attend a private school and less likely to work, suggesting that these decision can expand beyond educational expenditure at a particular point in time with potentially important longer-term effects.

I next turn to the more important question of whether elicited preferences are predictive of actual choices. To answer this question, I exploit the heterogeneity in preferences reported in the previous section and classify families as more or less inequality averse (depending on whether the estimated ρ_i is above or below the median value of ρ in the sample). In column 2 and 3 I report the results from this exercise. I find that those respondents that are identified as less inequality averse in the experiment, systematically make more unequal allocations when it comes to distribute actual resources. In particular, the point estimate in column 3 is twice as large as that in column 2 and statistically different from zero. This estimate implies that a 10 percent increase in the difference in endowments is associated with an increase in the educational expenditure gab between children of INR 470. This corresponds to 7 percent of the yearly educational expenditure. On the other hand, for families that are identified as more inequality averse a 10 percent increase in the endowments' difference increases the gap in educational expenditure only by 3.3 percent of the total yearly educational expenditure.

As a robustness check, I also experimented using two more "objective" measures of child endowments: whether the child suffered from any health condition in the first three years after birth and the health status of the child as reported by the primary caregiver (results available upon request). Both measures implied qualitatively similar results to those reported in Table 4. The fact that my experimentally elicited measures of parental prefereces maps into actual investment behaviour is reassuring, as it adds credibility to the research design, and to the use of hypothetical scenarios to identify structural parameters of interest.

7 Conclusions

This paper studies intra-household inequality in child human capital. I fist document that within household variation explains between 30 to 50 percent of overall inequality in child educational attainment. By looking at the human capital distribution within a family, I then show that while the human capital of high achieving children stays constant as family size increases, the human capital of children at the bottom of the achievement distribution steeply declines with family size. I argue that these patterns are informative about parental investment behaviour.

In order to understand the sources of intra-household inequality in child outcomes, I combine a theoretical model of household behaviour with a lab-in-the-field experiment. The model highlights the central role that parental investments have to explain inequality in child outcomes and how these investments choices depend on parental preferences, beliefs and financial resources. To mitigate the identification problem posed by observational data, I design and implement a lab-in-the-field experiment with parents of primary school children in India. I use a novel survey methodology based on hypothetical scenarios to collect data on subjective expectations and stated choices with and without financial constraints that allows me to identify the role of preferences, beliefs and constraints in determining household decisions.

Several key results emerge from this study. First, I find that parents perceive endowments and investments to be highly productive and that investments and endowments are complements in the production function of human capital. This suggests that parents should invest more in children with higher initial conditions in order to maximize the returns from their investments. Second, the experimental results reveal that parents have a low aversion to inequality over their children's outcomes and reinforce differences in child endowments. Specifically, I show that when the difference in child initial conditions increases parents re-allocate resources towards the higher achieving child, suggesting that investment choices are to some extent driven by efficiency considerations. Third, I show that financial constraints are important in explaining household investments, as parents reinforce more strongly initial conditions when per-capita resources are low. Because per-capita resource decrease with family size, this last results can explain the relation between family size and the distribution of child human capital. Finally, I show that experimentally elicited preferences relate to *actual* household behaviour. Specifically, respondents that are identified as less inequality averse in the experiment, systematically make more unequal allocations when it comes to distribute actual resources. This result adds credibility to the research design and to the use of hypothetical scenarios to identify structural parameters of interest.

The results in this paper indicate that early levels of human capital have a key role in driving inequality *within* the family, complementing previous research looking at their role in explaining inequality *between* families (Rubio-Codina, Attanasio, Meghir, Varela, & Grantham-McGregor (2015)). Children born with low initial levels of human capital are particularly penalized in two ways. First, through a biological channel coming from the human capital productions function. Second, they are penalized by parental allocative decisions which reinforce initial differences. This is particularly true in larger and poorer families, where parents might lack the resources to adequately investing in *all* their children.

These findings have important implications for policies aimed at reducing intra-household inequality. First, they suggest that acting on early levels of child human capital – potentially in the prenatal period – can reduce inequality within the household because parents would more equally distribute investment across their children. Moreover, the results highlight that because parental investment decisions are based on child endowments, early childhood investments not only generate large *direct* positive effects on child human capital as suggested by Heckman (2006) among others, but have the potential to produce important *indirect* effects through parental endogenous investment responses, thus magnifying the total returns. Finally, the findings point to the fact that relaxing credit-constraints can lead to more equal allocations within the family, resulting in improvements in child development, particularly for children with low initial levels of human capital. Future research should investigate how to incorporate parental endogenous responses to levels of child development into the design of effective policy interventions.

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Appendices

A Additional Tables and Figures

A.1 Tables

Outcome varibale: Log earnings at age 30	(1)	(2)
High endowment	0.860*	0.808*
	(0.056)	(0.056)
High investment	0.221*	0.169*
	(0.014)	(0.018)
Treatment	0.052	0.046
	(0.068)	(0.068)
High endowment × Treatment	-0.021	-0.009
	(0.058)	(0.060)
High Investment × Treatment	0.026	0.038
	(0.020)	(0.026)
High endowment × High investment	-	0.103*
		(0.019)
High endowment × High Investment × Treatment	-	-0.025
		(0.031)
Boy	0.147*	0.147*
	(0.053)	(0.053)
Observations	4960	4960

Notes: This table presents analogous coefficients and standard errors to those presented in Table 2 but with all the main regressors interacted with RCT treatment status. Because treatment status is allocated at the respondent level, regressions do not control for family fixed effects. The relevant comparison for column 1 is column 2 from Table 2 , and for column 2 is column 3 of Table 2. Robust standard error clustered at the family level are reported in brackets. * denotes 5% significance.

Table A.1: Effect of RCT Treatment Status on Perceived Human Capital Production Function

	Share of resources to child H	
	(1)	(2)
Difference in endowments	0.077*	0.109*
	(0.010)	(0.015)
Treatment	-0.004	-0.006
	(0.013)	(0.019)
Difference in endowments × Treatment	0.001	-0.014
	(0.014)	(0.021)
High resources	-	0.033*
		(0.011)
Difference in endowments × High resources	-	-0.064*
		(0.014)
High resources × Treatment	-	0.005
		(0.016)
Difference in endowments × High resources × Treatment		0.032
		(0.021)
Boy	0.006	0.006
	(0.011)	(0.011)
Observations	1980	1980

Notes: This Table presents analogous coefficients and standard errors to those presented in Table 3 but with all the main regressors interacted with RCT treatment status. Because treatment status is allocated at the respondent level, regressions do not control for family fixed effects. The relevant comparison for column 1 is column 1 from Table 3, and for column 2 is column 3 of Table 3 . Robust standard error clustered at the family level are reported in brackets. * denotes 5% significance.

Table A.2: Effect of RCT Treatment Status on Intra-household Allocation of Resources

Outcome varibale: Educational attainment (in years)	(1)	(2)	(3)	(4)
High endowment	2.042*	2.043*	2.039*	2.038*
	(0.046)	(0.056)	(0.056)	(0.048)
High investment	0.252*	0.252*	0.248*	0.248*
	(0.016)	(0.016)	(0.020)	(0.021)
Boy		0.002	0.002	-
		(0.062)	(0.062)	
High endowment x High investment			0.008	0.008
			(0.024)	(0.025)
Family fixed effects				✓
Observations	7920	7920	7920	7920

Notes: This table reports parent perceived returns. The outcome variable is educational attainment (in years) as perceived by the respondent. Columns 1 to 3 display the OLS results. Columns 4 further include family fixed effects. Robust standard error clustered at the family level are reported in brackets. * denotes 5% significance.

Table A.3: Perceived Human Capital Production Function (Educational Attainment)

Outcome varibale: Log earnings at age 30	Girls			Boys		
	(1)	(2)	(3)	(4)	(5)	(6)
High endowment	0.778*	0.729*	0.340*	0.758*	0.704*	0.401*
	(0.035)	(0.037)	(0.043)	(0.023)	(0.024)	(0.036)
High investment	0.250*	0.202*	0.157*	0.242*	0.187*	0.148*
	(0.012)	(0.015)	(0.014)	(0.013)	(0.016)	(0.015)
Hight endowment × High investment	-	0.097*	0.095*	-	0.109*	0.109*
		(0.019)	(0.018)		(0.018)	(0.018)
Belief about child education	-	-	0.189*	-	-	0.150*
			(0.017)			(0.018)
Family fixed effects		✓	✓		✓	✓
Observations	3968	3968	3968	3952	3952	3952

Notes: The table report coefficients analogous to those presented in Table 2 by splitting the sample according to the gender of the two children. The first 3 columns report the results for the sample of respondent who saw one boy and one girl, while the remaining 3 columns report results for the sample who saw two boys. The outcome variable is log-earnings of the child at age 30 as perceived by the respondent.Columns 1 and 4 display the OLS results. Columns 2, 3, 5 and 6 further include family fixed effects. Robust standard error clustered at the family level are reported in brackets. High endowment is a dummy variable that takes value 1 if in scenario j the child has an high initial skill level, High investment is a dummy variable that takes value one if in scenario j the level of investments is high. Belief about child education is the educational attainment respondents? believe the child will achieve in scenario j. * denotes 5% significance.

Table A.4: PERCEIVED HUMAN CAPITAL PRODUCTION FUNCTION BY GENDER

Outcome variable: total number of children	(1)
First born is girl	0.269***
	(0.010)
Orissa	-0.096***
	(0.037)
First born is girl × Orissa	-0.112**
	(0.055)
Mean	2.673
	(1.109)
Observations	37302

Notes: The outcome variable is total number of children. Controls include maternal education, household wealth, urban/rural indicator and religious group dummies. The estimation sample only includes mothers with completed fertility. * denotes 10% significance, ** denotes 5% significance, *** denotes 1% significance. Source: NFHS-4.

Table A.5: Gender and Family Size

Outcome variable:	Attends private school			Child works		
	All	Low ρ	High ρ	All	Low ρ	High ρ
	(1)	(2)	(3)	(4)	(5)	(6)
Difference in endowments	0.111*	0.111*	0.110*	-0.058*	-0.046*	-0.073*
	(0.011)	(0.016)	(0.016)	(0.005)	(0.007)	(0.006)
Mean outcome		0.201			0.149	
Observations	395	172	223	711	353	358

Notes: The outcome variable is the difference in investment between two children, in the outcome variable shown in the column header. Column 1 and 4 report the results in the full sample, while columns 2, 3, 5 and 6 report separate results for two separate sub-samples as defined by their inequality aversion (low ρ means higher inequality aversion). These two groups are defined based on whether the estimated ρ falls above or below the sample median. Robust standard error clustered at the family level are reported in brackets. Controls include child age and gender. $^{*}p < 0.05$

Table A.6: Actual Parental Investments: Additional Outcomes

A.2 Figures

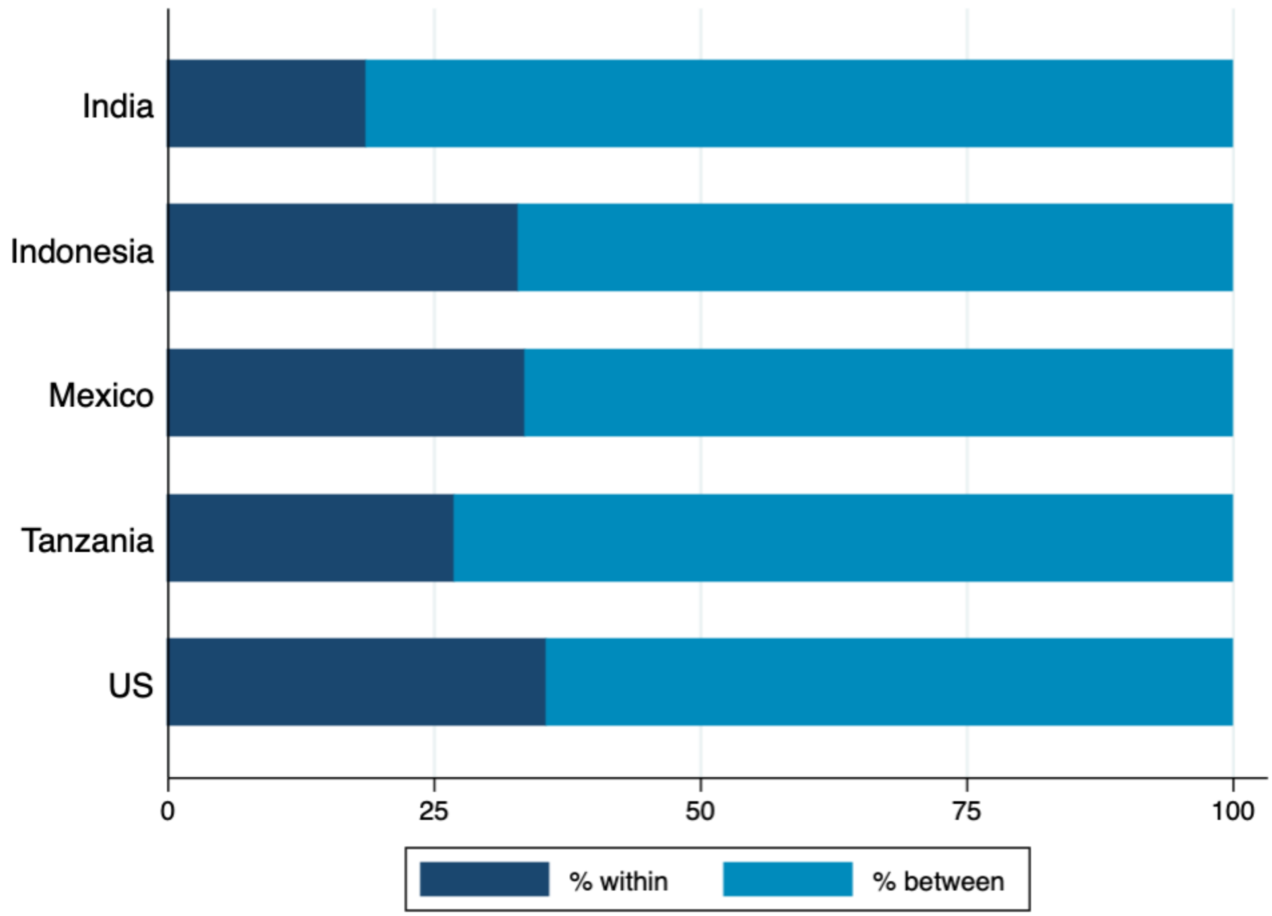


Figure A.1: Inequality in Child Human Capital (Test Scores)

Notes: This figure plots the within-household and between-households component of the Mean Log Deviation (MLD) measure of inequality. The outcome variable is age test scores. I use an age-standardized z-score, where the reference group consists of children in the same country and age. Thus coefficients are expressed in standard deviations units. Each bar represents a different country.

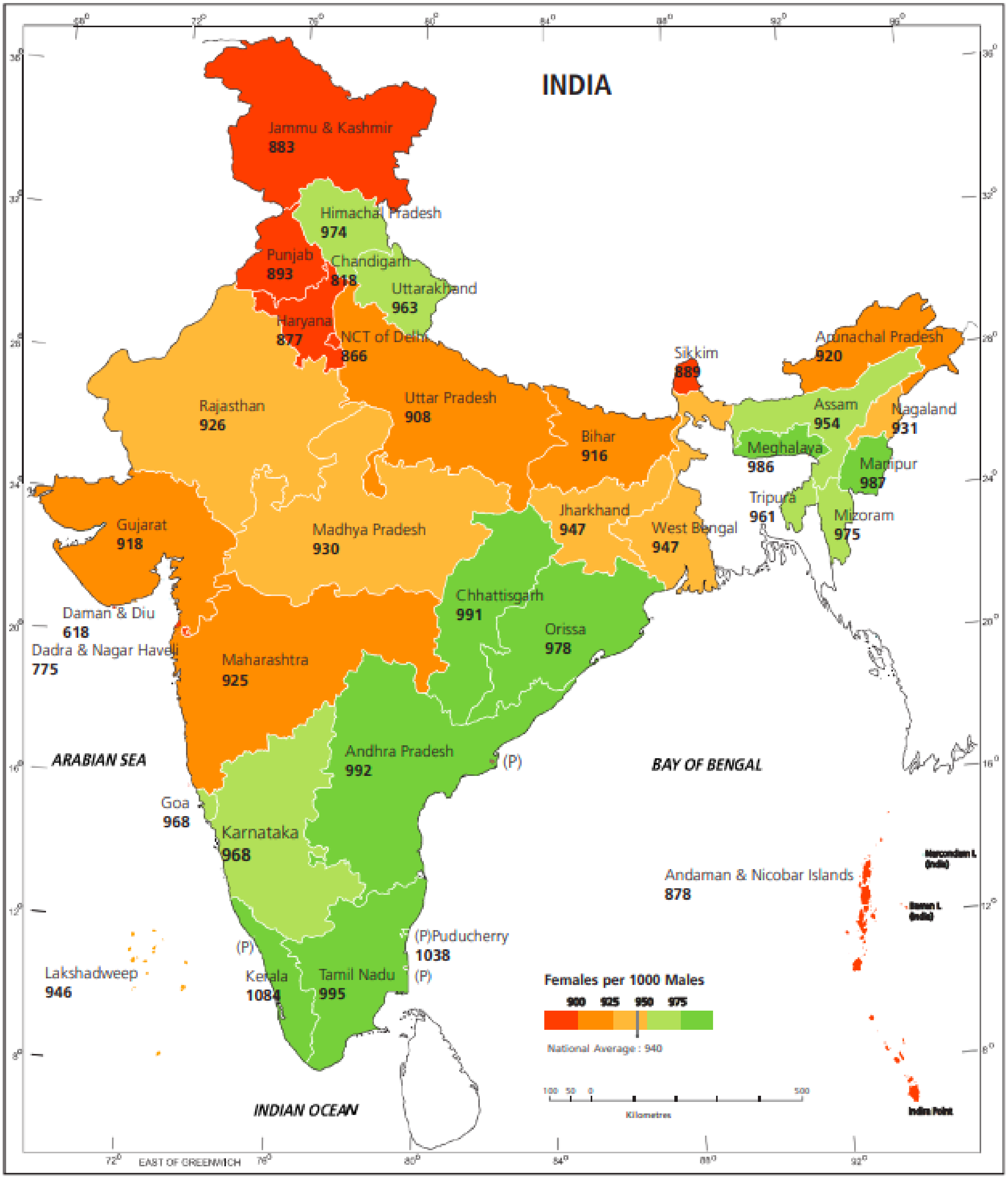


Figure A.2: Sex Ratio in India

Notes: This figure plots the sex ratio (girls per 1000 boys) across Indian states. Green areas represent states where the sex ratio is higher, while red and orange areas represent states with a lower sex ratio. The figure was downloaded from https://censusindia.gov.in/2011-prov-results/data_files/india/Final_PPT_2011_chapter5.pdf on the 10/09/2020. Source: Indian Census, 2011.

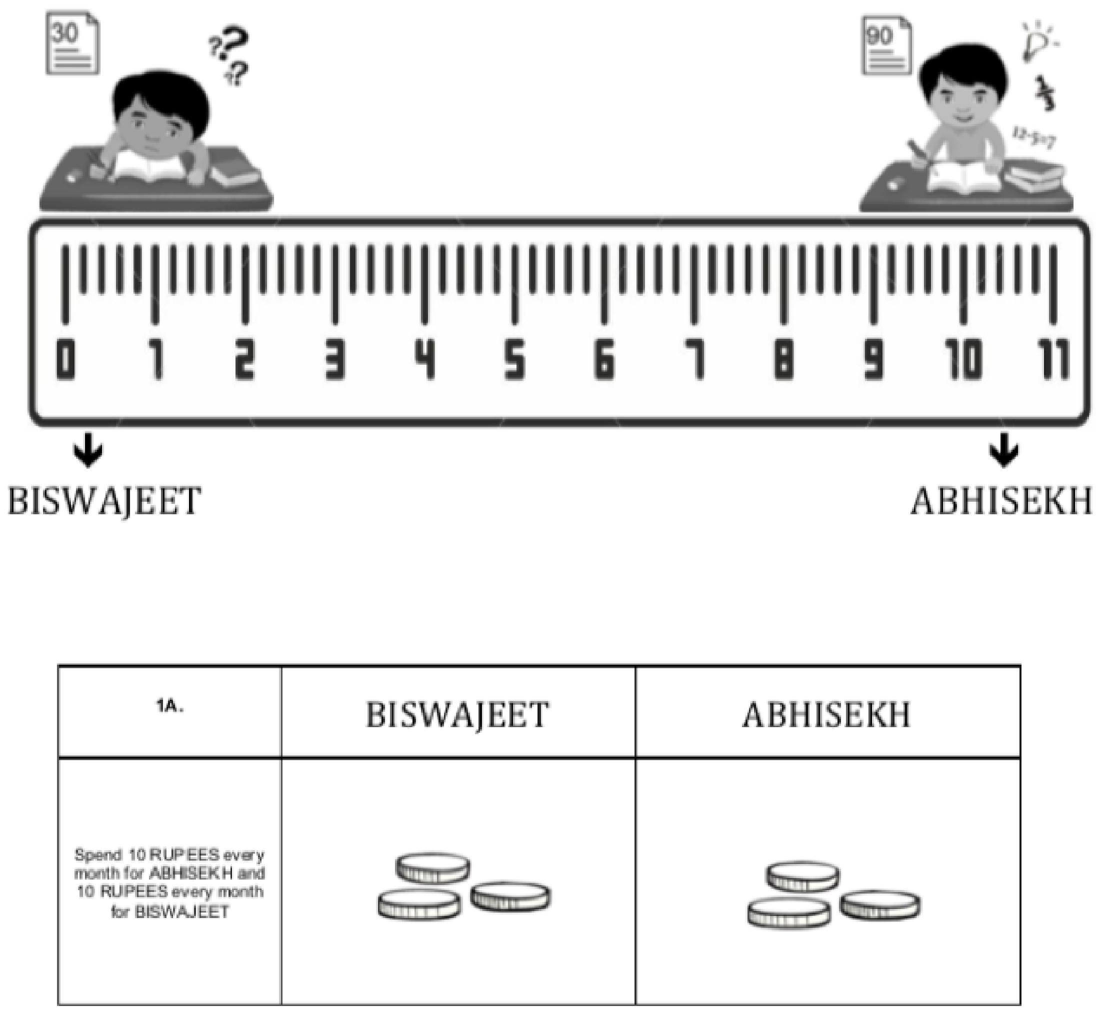
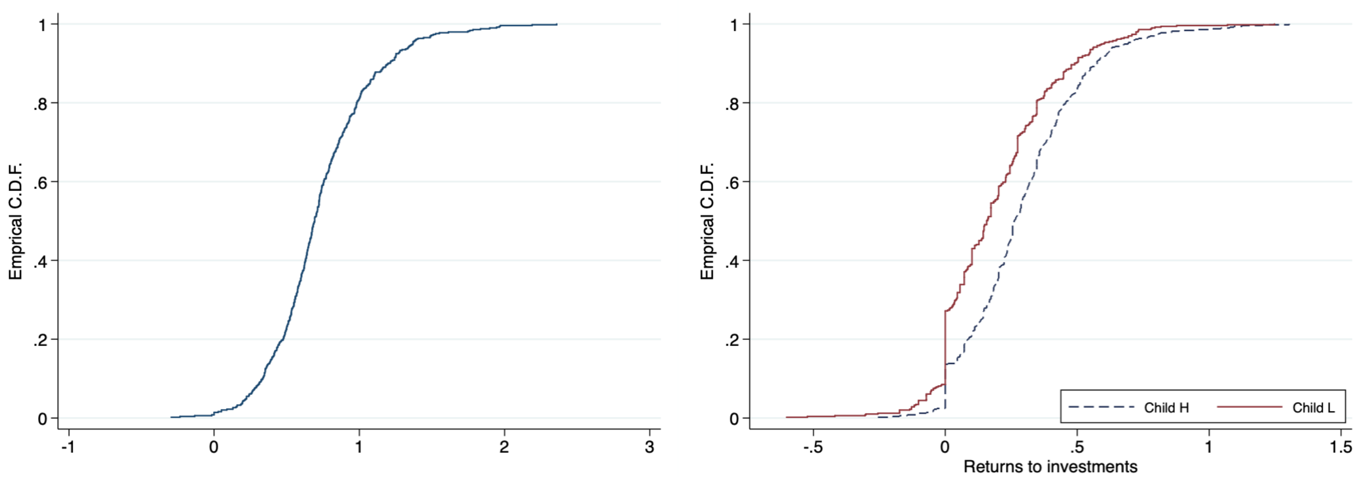


Figure A.3: Visual Aid

Notes: This figure shows an example of visual aid used to elicit parental beliefs about the human capital production function. Child initial skills (corresponding to endowments in the theoretical model) where described with the help of the ruler at the top of the figure. Parental investments where described using the coins at the bottom of the figure. In the example one child is described has having a low initial skill level, while the other child as having a high initial skill level. The level of investments in each child is low.



(A) Returns to endowment

(B) Returns to Investment

Figure A.4: Heterogeneity in Perceived Returns

Notes: This figure plots the empirical CDF of individual perceived returns. Panel A plot the CDF for the perceived return to endowments, while panel B the CDF for the perceived returns to investment. Panel B shows two CDFs. The solid one is for a child with low endowments, while the dashed one is for a child with high endowments.

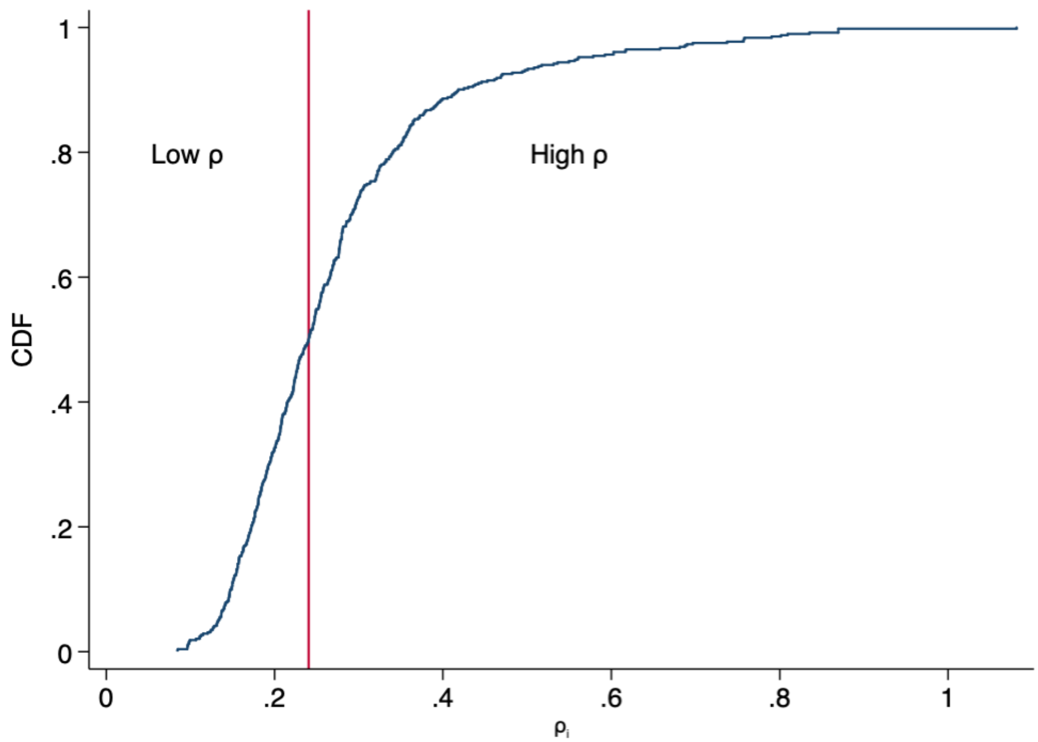


Figure A.5: Heterogeneity in Preferences

Notes: The figure plots the empirical density of parental preferences for intra-household inequality. The vertical line represents the median value of ρ in the sample. Low ρ households have greater concerns for intra-household inequality.

B Mean Log Deviation Measure of Inequality

Figure 1 and Figure 2 use the Mean Log Deviation Measure of Inequality (MLD) to decompose overall inequality in child human capital outcomes in a within-household and between-households components. The MLD can be expressed as:

$$MLD = \frac{1}{N}\sum_{i} ln\frac{\bar{y}}{y_i} \tag{B.1}$$

where y_i is individual outcome, $\bar{y}$ is average outcome among all individuals, and N is the total number of individuals. It can be shows that this measure can be decomposed into a within and between component as follows:

$$MLD = \sum_{j}\frac{N_j}{N}MLD_j + \sum_{j}\frac{N_j}{N}ln\frac{\bar{y}}{\bar{y_j}} \tag{B.2}$$

where N_j is the total size of group j, MLD_j is the mean log deviation measure of inequality in group j and $\bar{y_j}$ is the average outcome among all individuals in group j. The first term in the within-group component and the second the between-groups component (see Cowell (2011) for a formal derivation of this expression).

C Robustness Checks for Figure 2

This section provides several robustness checks for the relation between fertility and the distribution of human capital in the family shown in Figure 2.

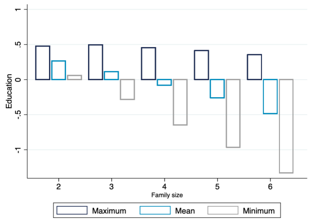
- Figure C.1 shows the relation between family size and the distribution of child quality using years of schooling as measure of quality. Each sub-plot represents a different country. The figure shows that the relation in Figure 2 holds across countries.

- Figure C.2 shows the relation between family size and the distribution of child quality using age standardized test scores as measure of quality. Each sub-plot represents a different country. The figure shows that the relation in Figure 2 holds across countries and is robust to the definition of child quality used.

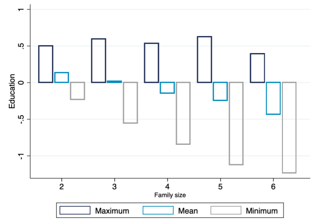
- Table C.1 report the regression results using age standardized test scores as measure of quality. In the table, I report the results of separate regression for the mean (columns 1 to 4), the maximum (columns 5 to 8) and the minimum (column 9 to 12). Columns 1, 5 and 9 include a linear indicator for family size. Columns 2, 6, and 10 include indicators for family size (ttop coded at size 6). Columns 3, 7 and 11 further control for birth order effects (top coded at birth order 6). Finally, columns 4, 8, and 12 include controls for mother and family background characteristics. All regressions control for child gender and age. Panel A shows the results for India, while Panel B reports results for the US. The Table shows that the results are not driven by background characteristics. The preferred specifications in columns 4, 8 and 12 (that control for child and family background characteristics) reveal a clear negative gradient in quality of the lowest achieving child in the family (column 12), and a shallow gradient in the quality of the highest achiever (column 8). Indeed, none of the family size dummies in column 8 is statistically different from zero and there is no clear patterns in the coefficients with some being negative while other positive. Comparing the coefficients in column 2 and 3, we can also infer that there is a negative birth order gradient in child human capital (the birth order dummies have been omitted to avoid clutter): once birth order is controlled for, the effect of family size on child outcomes becomes smaller in magnitude.

- Table C.2 report similar regression results as in Table C.1, but restricting the sample to women who have completed their fertility spell as identified in Jayachandran & Pande (2017). The outcome variable is age standardized test scores. Regressions control for birth order dummies, (top coded at birth order 6), child gender, child age and mother characteristics. These include maternal education dummies and location fixed-effects. All regressions control for child gender and child age. The Table confirms the results from Table C.1: there is a strong negative gradient in the minimum and a shallow gradient in the maximum.

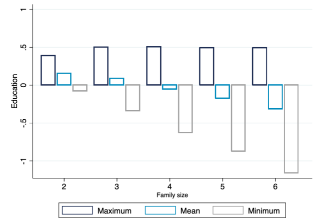
- Table C.3 reports the IV results using years of schooling as measure of quality. Family size is instrumented using twin birth as an instrument for total family size. In the table, I report separate regressions for the mean, the maximum and the minimum. Panel A reports the results for India, while panel B reports the results for the other developing countries shown in Figure C.1. I follow Angrist, Lavy, & Schlosser (2010) and report the results for the parity-pooled estimates to gain statistical power (i.e. I pool the 2+,3+, 4+ and 5+samples including first born in families with at least two births, first and second born in families with at least 3 births etc...). I account for missing instruments using the procedure introduced in Mogstad & Wiswall (2012). The Table confirms the results from Table C.1. There is a negative and significant effect of family size on the human capital of the lowest achieving child in the family, and a null effect on the human capital of the highest achieving child.



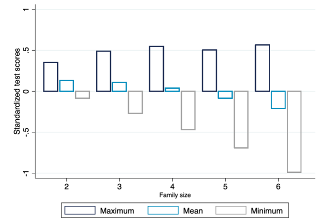
(A) India



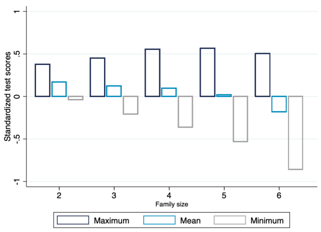
(B) US



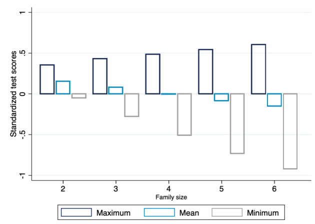
(C) Indonesia



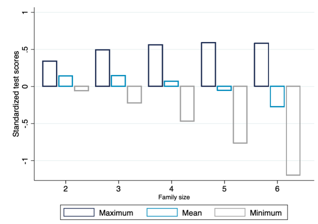
(D) Bolivia



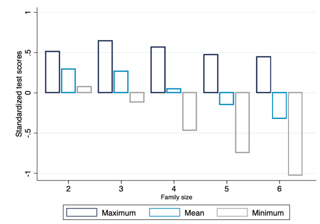
(E) Cameroon



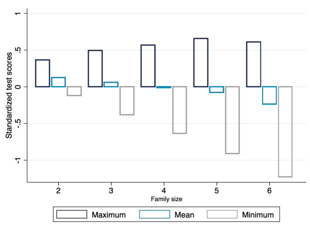
(F) Congo



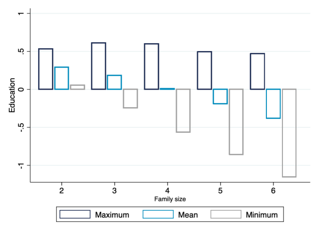
(G) Egypt



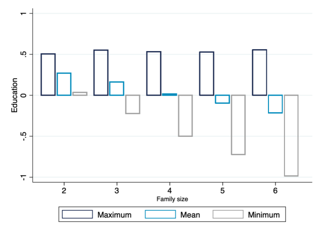
(H) Guatemala



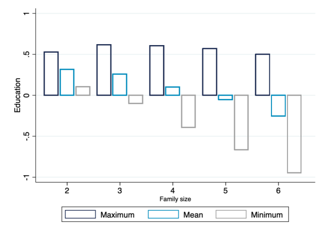
(I) Guyana



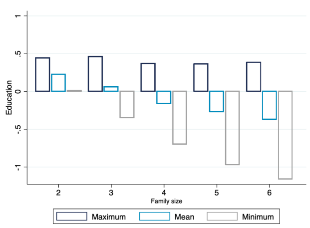
(J) Honduras



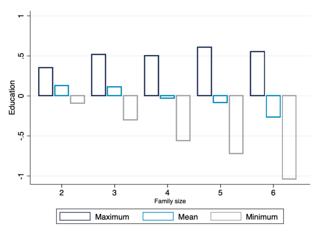
(K) Kenya



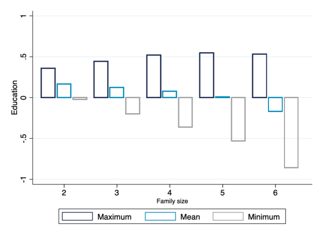
(L) Morocco



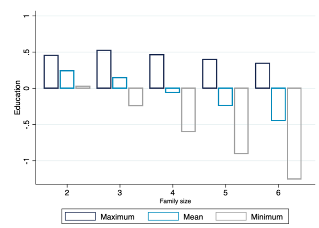
(M) Myanmar



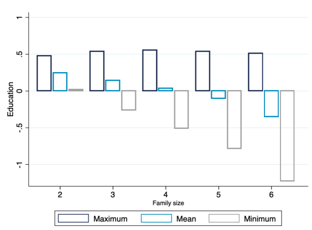
(N) Namibia



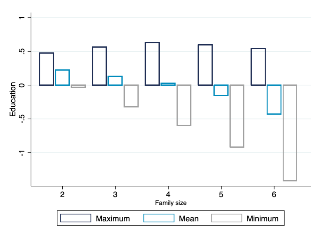
(O) Nigeria



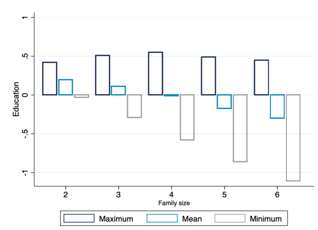
(P) Peru



(Q) Philippines



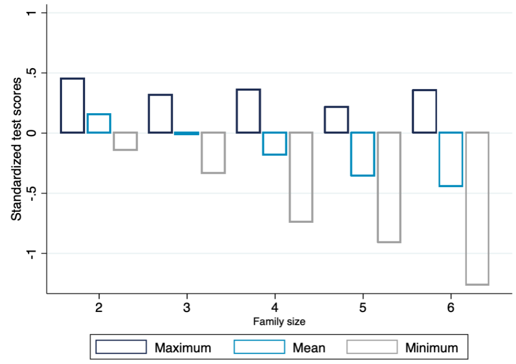
(R) Turkey



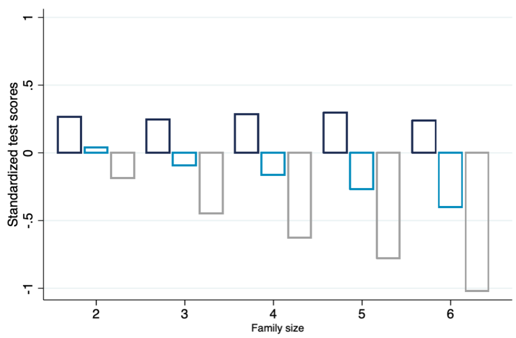
(S) Zimbabwe

Figure C.1: Fertility and Inequality in Child Human Capital (Educational Attainment)

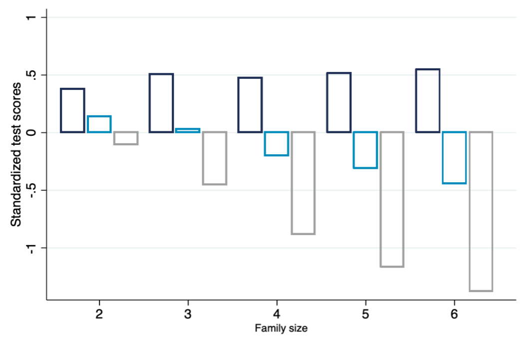
Notes: The figure shows the relationship between family size and the mean (light blue), the maximum (dark blue) and the minimum (grey) levels of human capital within the household. This figure is constructed as follows. For each family in the sample, I compute the maximum, minimum and mean levels of human capital achieved by children in that family. For each level of fertility, I then average across families. The outcome variable is educational attainment. I use an age-standardized z-score, where the reference group consists of children in the same country and birth cohort. Thus coefficients are expressed in standard deviations units.



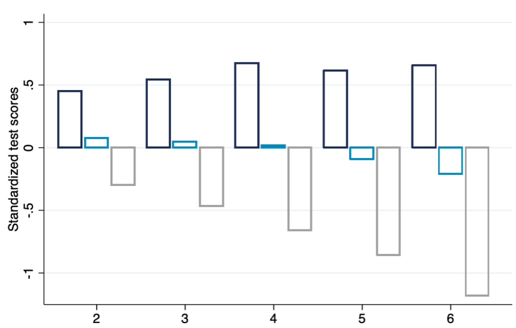
(A) India



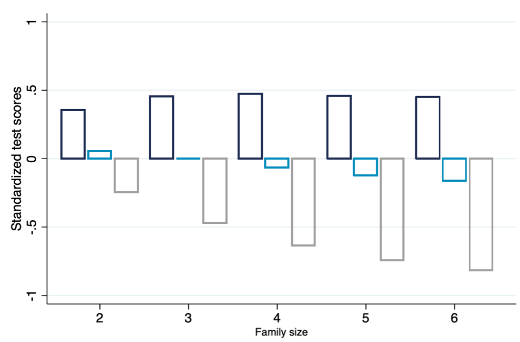
(B) US



(C) Mexico



(D) Indonesia



(E) Tanzania

Figure C.2: Fertility and Inequality in Child Human Capital (Test Scores)

Notes: The figure shows the relationship between family size and the mean (light blue), the maximum (dark blue) and the minimum (grey) levels of human capital within the household. This figure is constructed as follows. For each family in the sample, I compute the maximum, minimum and mean levels of human capital achieved by children in that family. For each level of fertility, I then average across families. The outcome variable is test scores. I use an age-standardized z-score, where the reference group consists of children in the same country and of the same age. Thus coefficients are expressed in standard deviations units. Details of the test used for every country are available in Appendix E.

	Mean				Maximum				Minimum			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: India												
Linear family size	-0.149*				-0.063*				-0.266*			
	(0.011)				(0.015)				(0.017)			
Family size dummies												
3 children		-0.146*	-0.110*	-0.002		-0.134*	-0.150*	-0.053		-0.192*	-0.110*	0.023
		(0.025)	(0.027)	(0.026)		(0.030)	(0.033)	(0.032)		(0.033)	(0.036)	(0.035)
4 children		-0.296*	-0.241*	-0.019		-0.091	-0.100	0.109		-0.597*	-0.495*	-0.239*
		(0.039)	(0.043)	(0.042)		(0.055)	(0.061)	(0.060)		(0.060)	(0.068)	(0.065)
5 children		-0.459*	-0.384*	-0.142*		-0.235*	-0.253*	-0.018		-0.767*	-0.620*	-0.356*
		(0.042)	(0.050)	(0.049)		(0.060)	(0.071)	(0.070)		(0.066)	(0.081)	(0.077)
6 children or more		-0.577*	-0.431*	-0.166*		-0.100	-0.170	0.082		-1.121*	-0.821*	-0.508*
		(0.067)	(0.087)	(0.084)		(0.112)	(0.140)	(0.136)		(0.123)	(0.167)	(0.157)
F-test		48.66	19.19	2.87		6.83	6.57	2.51		65.46	23.66	10.18
p-value†		0.00	0.00	0.02		0.00	0.00	0.04		0.00	0.00	0.00
Observations	6315	6315	6315	6291	3069	3069	3069	3057	3069	3069	3069	3057
Panel B: US												
Linear family size	-0.107*				0.002				-0.210*			
	(0.006)				(0.011)				(0.011)			
Family size dummies												
3 children		-0.129*	-0.111*	-0.061*		-0.019	-0.034	0.017		-0.258*	-0.275*	-0.215*
		(0.017)	(0.018)	(0.019)		(0.024)	(0.026)	(0.026)		(0.025)	(0.027)	(0.027)
4 children		-0.210*	-0.179*	-0.106*		0.020	0.007	0.058		-0.432*	-0.444*	-0.335*
		(0.021)	(0.023)	(0.024)		(0.033)	(0.036)	(0.038)		(0.034)	(0.039)	(0.040)
5 children		-0.301*	-0.276*	-0.153*		0.029	-0.036	0.137*		-0.588*	-0.592*	-0.471*
		(0.029)	(0.033)	(0.034)		(0.055)	(0.063)	(0.065)		(0.056)	(0.061)	(0.062)
6 children or more		-0.454*	-0.421*	-0.194*		-0.033	-0.076	0.099		-0.822*	-0.830*	-0.555*
		(0.032)	(0.039)	(0.041)		(0.068)	(0.080)	(0.083)		(0.069)	(0.085)	(0.092)
F-test		75.74	40.36	9.87		0.48	0.73	1.58		93.92	60.94	32.42
p-value†		0.00	0.00	0.00		0.75	0.57	0.18		0.00	0.00	0.00
Observations	8479	8479	8479	8479	3307	3307	3307	3307	3307	3307	3307	3307
Birth order dummies			✓	✓			✓	✓			✓	✓
Mother characteristics				✓				✓				✓

Table C.1: Effect of Fertility on the Distribution of Human Capital in the Family

Notes: The outcome variables are standardized test scores. Columns 1 to 4 display the results for average levels of human capital, pooling all children together. Columns 5 to 8 display the results for the maximum (i.e. one child per family). Columns 9 to 12 display the results for the minimum (i.e. one child per family). Columns 1, 5 and 9 includes a linear indicator of family size. Column 2, 6 and 10 includes total fertility dummies, top-coded at 6 children. Column 3, 7 and 11 includes total fertility dummies (top-coded at 6 children) and birth order dummies (top coded at birth order 6). Columns 4, 8 and 12 includes total fertility dummies (top-coded at 6 children), birth order dummies (top coded at birth order 6) and mother characteristics. This include maternal education dummies and location fixed-effects. All regressions control for child gender and child age. Standard errors are reported in brackets. † p-value of an F-test on the joint significance of the family size dummies. * denotes 5% significance.

	Mean	Maximum	Minimum
	(1)	(2)	(3)
Family size dummies			
3 children	0.050	-0.015	0.090
	(0.049)	(0.062)	(0.070)
4 children	0.006	0.116	-0.240
	(0.087)	(0.121)	(0.135)
5 children	-0.082	0.198	-0.376*
	(0.090)	(0.132)	(0.150)
6 children or more	-0.268*	0.056	-0.752*
	(0.130)	(0.198)	(0.292)
F-test	2.06	0.96	4.61
p-value†	0.08	0.43	0.00
Observations	3595	1109	1111

Notes: The outcome variables are standardized test scores. The sample used in these regression is the same as that used in Jayachandran & Pande (2017). All regressions include total fertility dummies (top-coded at 6 children), birth order dummies (top coded at birth order 6) and mother characteristics. These include maternal education dummies and location fixed-effects. All regressions control for child gender and child age. Standard errors are reported in brackets. † p-value of an F-test on the joint significance of the family size dummies. * denotes 5% significance.

Table C.2: Effect of Fertility on the Distribution of Human Capital in the Family - Completed Fertility Sample

	OLS			IV		
Panel A: India	Mean	Maximum	Minimum	Mean	Maximum	Minimum
Linear family size	-0.081*	0.003	-0.163*	-0.053	-0.000	-0.156*
	(0.001)	(0.002)	(0.002)	(0.031)	(0.024)	(0.025)
Observations	366031	160199	153066	366031	160199	153066
Panel B: Developing countries						
Linear family size	-0.043*	0.025*	-0.112*	0.004	0.020	-0.050*
	(0.001)	(0.001)	(0.001)	(0.028)	(0.015)	(0.017)
Observations	393215	177587	169086	393215	177587	169086

Notes: The outcome variable is years of schooling (age-standardized z-score). The reference group consists of children in the same country and birth cohort. In each regression we pool the 2+, 3+, 4+ and 5+ samples together (as defined in Angrist, Lavy, & Schlosser (2010)). Columns 1 to 3 display the OLS results and columns 4 to 6 display the IV results. All regressions control for child gender, child age, child age squared, mother year of birth, household wealth index and maternal education. Standard errors are reported in brackets. Panel A reports the results for India, while Panel B reports the results pooling the set of developing countries in Figure C.1 together. This includes Bolivia, Cameroon, Congo, Egypt, Guatemala, Guyana, Honduras, Indonesia, Kenya, Morocco, Myanmar, Namibia, Nigeria, Peru, Philippines, Turkey and Zimbabwe. * denotes 5% significance.

Table C.3: Effect of Fertility on the Distribution of Human Capital in the Family - IV

D Model Appendix

D.1 Close form solution for investments

In this section, I derive a closed form solution for investments. Maximizing (1) subject to (2) and (6) one can get to the following closed form solution for investments in child i:

$$X_i^* = y \frac{\theta_i^{\frac{a\rho}{1-b\rho}}}{\sum_{j=1}^{n} \theta_j^{\frac{a\rho}{1-b\rho}}} \tag{D.1}$$

Computing the ration of X_i^* to X_j^* and taking the log we get equation (7).

D.2 For sufficiently high values of γ investments in the highest endowment child are not sensitive to family size

In this section for sufficiently high values of γ, the child with the highest endowment will receive roughly the same share of household resources independently of family size. I define the largest endowment in the family as θ_{max}. For any family size n, the model implies that educational investments in the highest endowment child are:

$$X_{max}^*(n) = y \frac{\theta_{max}^{\frac{a\rho}{1-b\rho}}}{\underbrace{\theta_{min}^{\frac{a\rho}{1-b\rho}} + ... + \theta_{max}^{\frac{a\rho}{1-b\rho}}}_{\text{n terms}}} = y \frac{\theta_{max}^{\gamma}}{\theta_{min}^{\gamma} + ... + \theta_{max}^{\gamma}} \tag{D.2}$$

As n increases, there competition over household resources increases. This can be seen from the increase in the number of terms on the denominator of expression (D.2). As $\gamma \to \infty$:

$$\lim_{\gamma\to\infty} X_{max}^*(n) = \lim_{\gamma\to\infty} y \frac{1}{\left(\frac{\theta_{min}}{\theta_{max}}\right)^{\gamma} + ... + 1} = y \tag{D.3}$$

This is because the first $n-1$ terms in the denominator are smaller than one. The result holds for all values of n so that $X_{max}^*(n) \to X_{max}^*(n+1)$.

Intuition Figure D.1 provides the intuition behind this mechanisms. The top panels plot γ on the x-axis and the share of total resources allocated to an high endowment child (left panel) and a low endowment child (right panel) on the y-axis. In each plot there are two lines: the blue line represents the share of resources the child receives in a family with n children, while the black line represents the share she receives in a family with $n+1$ children. The graph shows that when γ increases the share of resources devoted to θ_H increases, while the share of resources devoted to θ_L decreases. Interestingly, as γ increases the shares of resources allocated to each child in families of different sizes converge.

The bottom panels plot the *change* in shares as we move from a family with n to $n+1$ children. This corresponds to the vertical distance between two lines in the corresponding top panel. The figures show that as family size increases low endowment children are more penalized than high endowment children in terms of resources, because of more competition implied by a larger family size. This result, coupled with the existence of decreasing returns to investments, explains why as family size increases there is a shallow gradient in maximum child quality and a steep drop in the quality of the lowest achieving child.[34,35]

D.3 Fertility stopping rule

In this section, I derive the fertility stopping rule for parental fertility choices. Assume that parents first decide sequentially on the number of children they have. Once the fertility spell is concluded, they decide how to allocate educational investments. The model can be solved backwards. The optimal allocation of investments in the second stage will be the same as that in the standard model. In each period parents compare the utility from having n children with the expected utility of having $n+1$ children. They will stop when the former is greater than the latter, that is:

$$U(n) > \mathbb{E}[U(n+1)]$$

$$y^b\Big(\sum_{i=1}^{n}\theta_j^{\frac{\rho}{1-b\rho}}\Big)^{\frac{1-b\rho}{\rho}} > y^b\int_{\theta_{n+1}}\Big(\sum_{i=1}^{n+1}\theta_j^{\frac{\rho}{1-b\rho}}\Big)^{\frac{1-b\rho}{\rho}}\mathcal{F}(\theta_{n+1})d\theta_{n+1} \tag{D.4}$$

where $\mathcal{F}(.)$ is the distribution from which endowments are drawn. This expression can be derived by plugging the optimal investment level in the human capital production function, and substitute that in the parental utility function. Figure D.2, plots the utility of having n children (in black) and the expected utility of having $n+1$ children (in blue) as a function of θ_n. These correspond to the left hand side and right hand side of equation (D.4).

Case $\rho > 0$. As θ_n increases the utility from having n children becomes larger than the expected utility of having an additional child. This implies that parents become increasingly more likely to stop having children.In this case, the model predict that low endowment children are more likely to belong to larger families.

Case $\rho < 0$. For all values of θ_n the utility of having n children is always greater than the expected utility of having an additional child. This means that parents will never want to increase their fertility level. Below I formally show that inequality averse parents will never want to have more than one child in this case.

[34] Decreasing marginal product of investments means that a reduction in investments will have a much larger impact on child human capital when it happens at a low baseline level of investments, that when it happens at a high baseline level.

[35] Consider the following example: when $\gamma = 0.5$, θ_H receives roughly 50% of resources in a family with three children, while θ_L received around 25%. As family size increases to four, θ_H will continue receiving about the same, while θ_L will now get only 5% of total resources. This reduction is both large in magnitude and happens at a low baseline level of resources, implying a potentially large and negative impact on the human capital of this child.

D.4 Inequality averse parents will not exceed their target fertility level

This section shows that parents will never want to exceed their desired fertility level when $\rho < 0$. I want to show that the utility of having one child is greater than the expected utility of having two children. This is:

$$y^{\alpha}(\theta_1^{\frac{\rho}{1-\alpha\rho}})^{\frac{1-\alpha\rho}{\rho}} > y^{\alpha}\int_{\theta_2}(\theta_1^{\frac{\rho}{1-\alpha\rho}} + \theta_2^{\frac{\rho}{1-\alpha\rho}})^{\frac{1-\alpha\rho}{\rho}}\mathcal{F}(\theta_2)d\theta_2 \tag{D.5}$$

This can be expressed as:

$$(\theta_1^{\frac{\rho}{1-\alpha\rho}})^{\frac{1-\alpha\rho}{\rho}} > \int_{\theta_2}(\theta_1^{\frac{\rho}{1-\alpha\rho}} + \theta_2^{\frac{\rho}{1-\alpha\rho}})^{\frac{1-\alpha\rho}{\rho}}\mathcal{F}(\theta_2)d\theta_2 \tag{D.6}$$

Using the fact that when $\rho < 0$, then $\frac{1-\alpha\rho}{\rho} < 0$ and $\frac{\rho}{1-\alpha\rho} < 0$, one can show that the right hand side term is a decreasing function of θ_2. Let $\theta_1^{\frac{\rho}{1-\alpha\rho}} \equiv \Psi$. Then, $\frac{\partial(\Psi+x)^{\frac{1-\alpha\rho}{\rho}}}{\partial x} < 0$ for all positive x. So that the left hand side is always greater that the right hand side. Therefore inequality averse parents will never have more than one child.[36]

D.5 Fertility

When fertility is considered endogenous, the model makes a testable prediction about household behaviour. In particular, by the fertility stopping mechanism the model predicts that parents are more likely to continue having children after giving birth to a low endowment child, than when they have a child with an high endowment. I test this prediction using observational data from the National Family Health Survey (NFHS). The NFHS is a repeated cross-sectional data set based on the Demographic and Health Survey. The NFHS surveys a representative sample of ever-married women aged between 15 to 49 across India.[37]

One reason for using this data istead of the experimental sample to test this model prediction is that, as discussed in section 5, respondents in the sample are still relatively young (the average age of the respondent is 28 years old). For this reason, families might still be at the beginning of their fertility spell, so that the relation between endowments and fertility would be confounded.Therefore, in the preferred specifications I only include women who report being infertile or sterilized as these are more likely to have concluded their fertility spell.

To analyse the relation between child endowments and fertility, I estimate variants of the following empirical specification:

$$Y_{ij} = \alpha_0 + \alpha_1\theta_i + \alpha_2 X_{ij} + u_{ij} \tag{D.7}$$

where i is the child, and j is the mother, and the outcomes Y_{ij} is indicator for whether the mother had another child after the birth of child i. The variable θ_i is a measure of child endowments, and X_{ij} is a vector of child and mother characteristics including birth order, child gender, ideal family size and maternal education. Child endowment is measured using a survey question asking respondents about the

[36]The model can also be extended to allow parents to have a target fertility level n^*. In that case, one can show that this condition hold for $n = n^*$, so that inequality averse parents never have more than n^* children.

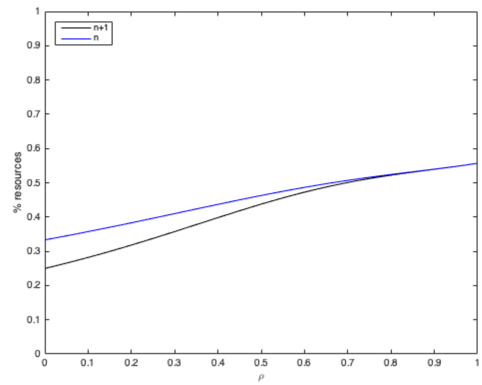
[37]Details about the data and descriptive statistics of the NFHS sample can be found in Appendix E.

perceived size of their child at birth.[38] Answers range from "very small" to "very large". According to the model prediction we should expect $\alpha_1 < 0$, as parents are more likely to stop having children after the birth of an high endowment child.

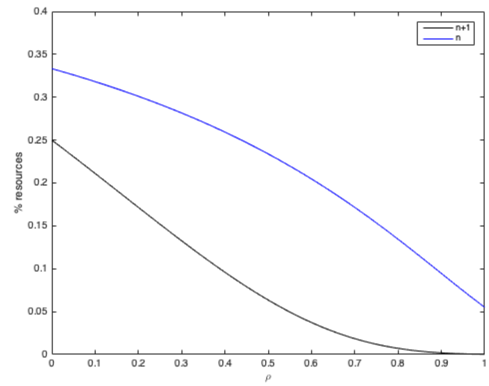
Figure D.3 plots child endowment on the horizontal axis and the estimated coefficients on the endowments dummy variables on the vertical axis (the excluded category is "very small"). I show the coefficients from both an OLS and a Logit model. The figure shows that the pattern of coefficients is similar regardless of which specification is used: fertility decreases monotonically with child endowment. Table D.1 report the regression results. Columns 1 to 4 report the OLS results, while column 5 report the Logit results in terms of odds-ratios. All regressions control for child gender, birth order, and state fixed-effects. Column 2 further controls linearly for ideal family size (at the time of the survey), while column 3 control non-linearly for distance from ideal family size. Finally column 4 and 5 only report results for the sample of women who report having completed their fertility spell or being sterilized. The preferred specification in column 4 implies that, relatively to families whose child endowment is "very small", parents who give birth to a child whose endowment is "very large" are 4.6 percentage points more likely to stop having children.

These results are robust to several robustness checks. First, the measure of endowments used in the analysis is a perception that parents have about child endowment. As different families might have different benchmarks against which they evaluate child size, I show that these results hold using a more objective measure of child endowment (see Appendix Table D.4). I also replicate the same pattern in a US sample for which I have objective and detailed information about child birth weight that I use to measure child birth endowments (see Appendix Table D.5). Another advantage of the US data is that desired fertility is collected prior to the start of the fertility spell. This avoids the problems associated with retrospective questions (Rosenzweig & Wolpin (1993). Finally, I show that these results are still apparent if I use as alternative outcome for fertility the probability of parents exceeding their target fertility level (see in Appendix Table D.6).

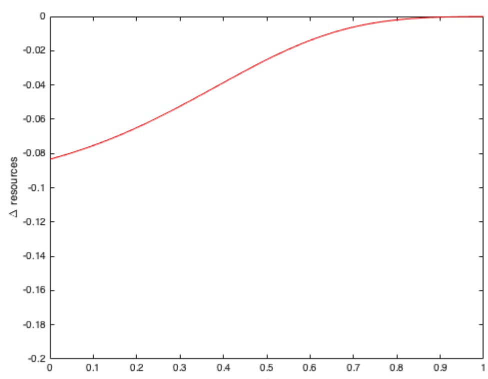
[38]The exact wording of the question can be found in Appendix E.



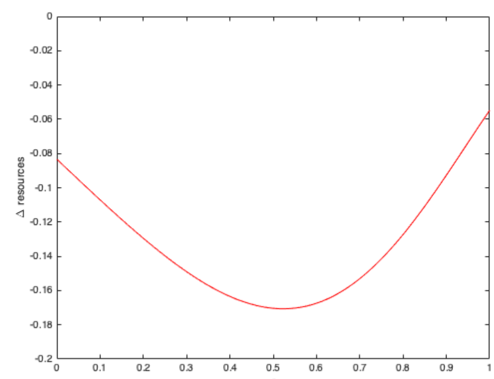
(A) Share of total resources - θ_H



(B) Share of total resources - θ_L



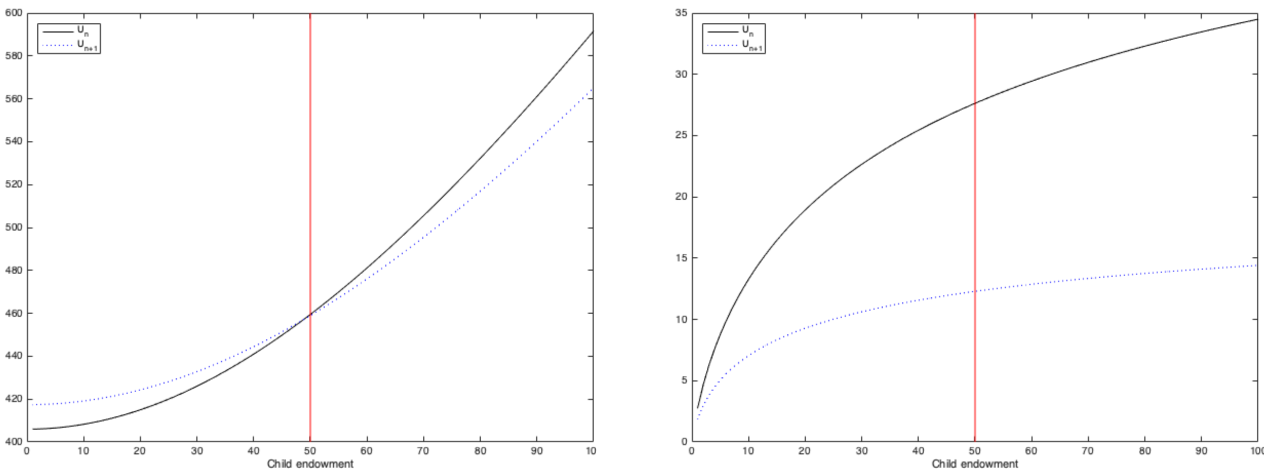
(C) Change in shares - θ_H



(D) Change in shares - θ_L

Figure D.1: Family Size, Preferences and Investments

Notes: The top two panels plot the share of total resources devote to child θ_H (panel A) and θ_L (panel B) as a function of ρ for families with n children (in blue) vs $n+1$ children (in black). On the x-axis there is ρ, while on the y-axis there is the share of total household resources. The middle two panels plot the corresponding change in shares as we move from a family with n children to a family with $n+1$ children as a function of ρ, separately for child θ_H (panel C) and child θ_L (panel D). On the x-axis there is ρ, while on the y-axis there is the change in shares.



(A) $\rho > 0$ (B) $\rho < 0$

Figure D.2: Fertility Stopping Rule

Notes: The figure show the left hand side and right hand side of equation (D.4) for different values of θ_3, holding fixed θ_1 and θ_2. Panel (a) shows the case where $\rho > 0$, while panel (b) the case $\rho < 0$.

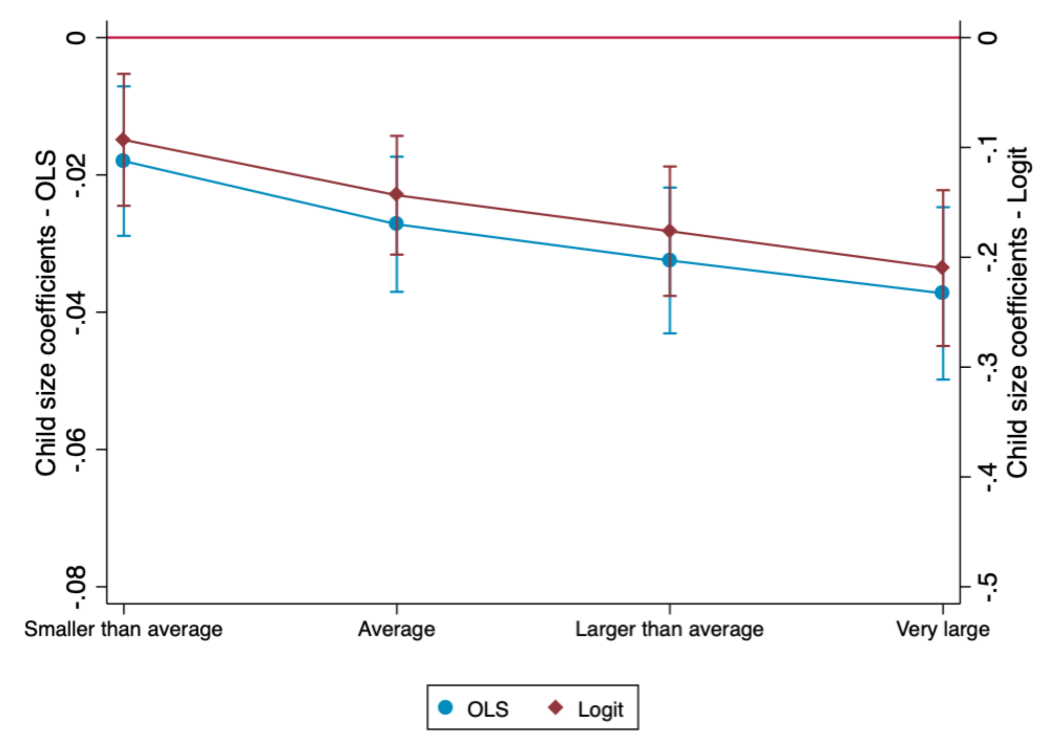


Figure D.3: Fertility and Child Endowments

Notes: The outcome variable is an indicator variable for whether the mother had another child after child i. The figure plots child endowment (categorical values) on the horizontal axis and the estimated coefficients on the endowments dummy variables on the vertical axis. The excluded category for child endowments is "very small". The left axis plots the coefficients from an OLS model and the right axis the coefficients from a Logit model. The models includes dummy variables for child birth order, ideal family size, maternal education, state fixed effects, urban/rural indicator and religion fixed effects.

Outcome variable: mother has an additional child	(1)	(2)	(3)	(4)	(5)
Child endowment:					
Very large	-0.039***	-0.037***	-0.038***	-0.046***	0.711***
	(0.005)	(0.006)	(0.006)	(0.013)	(0.070)
Larger than average	-0.028***	-0.032***	-0.032***	-0.037***	0.768***
	(0.004)	(0.005)	(0.005)	(0.012)	(0.067)
Average	-0.020***	-0.027***	-0.028***	-0.033***	0.792***
	(0.004)	(0.005)	(0.005)	(0.011)	(0.065)
Smaller than average	-0.013***	-0.018***	-0.019***	-0.005	0.971
	(0.004)	(0.006)	(0.006)	(0.013)	(0.088)
Child is boy	-0.051***	-0.047***	-0.042***	-0.033***	0.778***
	(0.001)	(0.002)	(0.002)	(0.004)	(0.021)
Maternal education		-0.009***	-0.009***	-0.010***	0.931***
		(0.001)	(0.001)	(0.001)	(0.008)
Birth order:					
2	-0.124***	-0.155***	-0.029***	-0.653***	0.038***
	(0.002)	(0.002)	(0.003)	(0.005)	(0.001)
3	-0.138***	-0.191***	-0.030***	-0.733***	0.020***
	(0.002)	(0.003)	(0.003)	(0.006)	(0.001)
4	-0.140***	-0.213***	-0.009*	-0.763***	0.016***
	(0.003)	(0.004)	(0.005)	(0.008)	(0.001)
5	-0.130***	-0.220***	0.015**	-0.793***	0.012***
	(0.003)	(0.006)	(0.007)	(0.011)	(0.001)
6 or higher	-0.133***	-0.234***	0.055***	-0.794***	0.012***
	(0.003)	(0.006)	(0.008)	(0.013)	(0.001)
Ideal family size		0.062***		0.072***	1.674***
		(0.001)		(0.002)	(0.029)
Controls		✓	✓	✓	✓
Complete fertility sample				✓	✓
Observations	385006	241004	241004	43166	43157

Notes: The outcome variable is an indicator for whether the mother had another child after child i. Columns 1 to 4 report the OLS results, while columns 5 the logit results, in terms of odds ratios. All regressions control for child gender, child birth order (truncated at 6), state fixed effects and urban/rural indicator. Controls include religion fixed effects, ideal family size and mother education in years. Column 2 controls linearly for ideal family size, while column 3 includes dummies for distance from ideal family size (omitted category is 0). The coefficients on distance from ideal family size are omitted from the table, but available in Appendix Table D.2. Complete fertility sample only includes women who report being infertile or sterilized.
* denotes 10% significance, ** denotes 5% significance, *** denotes 1% significance.

Table D.1: Fertility and Child Endowments

Outcome variable: mother has an additional child	(1)	(2)	(3)	(4)	(5)
Child endowment:					
Very large	-0.039***	-0.037***	-0.038***	-0.046***	0.711***
	(0.005)	(0.006)	(0.006)	(0.013)	(0.070)
Larger than average	-0.028***	-0.032***	-0.032***	-0.037***	0.768***
	(0.004)	(0.005)	(0.005)	(0.012)	(0.067)
Average	-0.020***	-0.027***	-0.028***	-0.033***	0.792***
	(0.004)	(0.005)	(0.005)	(0.011)	(0.065)
Smaller than average	-0.013***	-0.018***	-0.019***	-0.005	0.971
	(0.004)	(0.006)	(0.006)	(0.013)	(0.088)
Child is boy	-0.051***	-0.047***	-0.042***	-0.033***	0.778***
	(0.001)	(0.002)	(0.002)	(0.004)	(0.021)
Maternal education		-0.009***	-0.009***	-0.010***	0.931***
		(0.001)	(0.001)	(0.001)	(0.008)
Birth order:					
2	-0.124***	-0.155***	-0.029***	-0.653***	0.038***
	(0.002)	(0.002)	(0.003)	(0.005)	(0.001)
3	-0.138***	-0.191***	-0.030***	-0.733***	0.020***
	(0.002)	(0.003)	(0.003)	(0.006)	(0.001)
4	-0.140***	-0.213***	-0.009*	-0.763***	0.016***
	(0.003)	(0.004)	(0.005)	(0.008)	(0.001)
5	-0.130***	-0.220***	0.015**	-0.793***	0.012***
	(0.003)	(0.006)	(0.007)	(0.011)	(0.001)
6 or higher	-0.133***	-0.234***	0.055***	-0.794***	0.012***
	(0.003)	(0.006)	(0.008)	(0.013)	(0.001)
Ideal family size		0.062***		0.072***	1.674***
		(0.001)		(0.002)	(0.029)
Distance from ideal family size:					
-6			0.188***		
			(0.017)		
-5			0.178***		
			(0.015)		
-4			0.263***		
			(0.012)		
-3			0.312***		
			(0.007)		
-2			0.287***		
			(0.004)		
-1			0.159***		
			(0.003)		
1			0.017***		
			(0.003)		
2			-0.011**		
			(0.005)		
3			-0.021**		
			(0.008)		
4			-0.022		
			(0.014)		
5			-0.025		
			(0.032)		
6			-0.055		
			(0.041)		
Controls		✓	✓	✓	✓
Complete fertility sample				✓	✓
Observations	385006	241004	241004	43166	43157

Notes: The outcome variable is an indicator for whether the mother had another child after child *i*. Columns 1 to 4 report the OLS results, while columns 5 the logit results, in terms of odds ratios. All regressions control for child gender, child birth order (truncated at 6), state fixed effects and urban/rural indicator. Controls include religion fixed effects, ideal family size and mother education in years. Column 2 controls linearly for ideal family size, while column 3 includes dummies for distance from ideal family size (omitted category is 0). Complete fertility sample only includes women who report being infertile or sterilized. * denotes 10% significance, ** denotes 5% significance, *** denotes 1% significance. Source: NFHS.

Table D.2: Fertility and Child Endowments (Full Results)

Outcome variable: mother has an additional child	(1)	(2)	(3)	(4)	(5)
Size of child is small	0.012***	0.014***	0.014***	0.030***	0.221***
	(0.002)	(0.002)	(0.002)	(0.005)	(0.040)
Child is boy	-0.051***	-0.047***	-0.042***	-0.033***	-0.251***
	(0.001)	(0.002)	(0.002)	(0.004)	(0.027)
Maternal education		-0.009***	-0.009***	-0.010***	-0.072***
		(0.001)	(0.001)	(0.001)	(0.008)
Birth order:					
2	-0.124***	-0.155***	-0.029***	-0.653***	-3.267***
	(0.002)	(0.002)	(0.003)	(0.005)	(0.037)
3	-0.138***	-0.191***	-0.030***	-0.733***	-3.892***
	(0.002)	(0.003)	(0.003)	(0.006)	(0.046)
4	-0.139***	-0.213***	-0.008*	-0.763***	-4.144***
	(0.003)	(0.004)	(0.005)	(0.008)	(0.062)
5	-0.130***	-0.220***	0.015**	-0.793***	-4.413***
	(0.003)	(0.006)	(0.007)	(0.011)	(0.091)
6 or higher	-0.133***	-0.234***	0.056***	-0.794***	-4.414***
	(0.003)	(0.006)	(0.008)	(0.013)	(0.105)
Ideal family size		0.062***		0.072***	0.516***
		(0.001)		(0.002)	(0.017)
Distance from ideal family size:					
-6			0.188***		
			(0.017)		
-5			0.178***		
			(0.015)		
-4			0.263***		
			(0.012)		
-3			0.312***		
			(0.007)		
-2			0.287***		
			(0.004)		
-1			0.159***		
			(0.003)		
1			0.017***		
			(0.003)		
2			-0.011**		
			(0.005)		
3			-0.021**		
			(0.008)		
4			-0.022		
			(0.014)		
5			-0.025		
			(0.032)		
6			-0.055		
			(0.041)		
Controls		✓	✓	✓	✓
Complete fertility sample				✓	✓
Observations	385006	241004	241004	43166	43157

Notes: The outcome variable is an indicator for whether the mother had another child after child *i*. Columns 1 to 4 report the OLS results, while columns 5 the logit results, in terms of odds ratios. All regressions control for child gender, child birth order (truncated at 6), state fixed effects and urban/rural indicator. Controls include religion fixed effects, ideal family size and mother education in years. Column 2 controls linearly for ideal family size, while column 3 includes dummies for distance from ideal family size (omitted category is 0). Complete fertility sample only includes women who report being infertile or sterilized. * denotes 10% significance, ** denotes 5% significance, *** denotes 1% significance. Source: NFHS.

Table D.3: Fertility and Child Endowments (Binary Endowments)

Outcome variable: mother has an additional child	(1)	(2)	(3)	(4)	(5)
Child died	0.192***	0.216***	0.212***	0.175***	1.382***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.020)
Child is boy	-0.069***	-0.079***	-0.073***	-0.084***	-0.553***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.008)
Education years mother		-0.017***	-0.015***	-0.011***	-0.080***
		(0.000)	(0.000)	(0.000)	(0.002)
Birth order:					
2	-0.179***	-0.257***	-0.035***	-0.393***	-3.071***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.014)
3	-0.243***	-0.349***	-0.072***	-0.542***	-3.857***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.015)
4	-0.272***	-0.396***	-0.046***	-0.601***	-4.235***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.018)
5	-0.285***	-0.420***	-0.029***	-0.637***	-4.483***
	(0.001)	(0.003)	(0.003)	(0.004)	(0.024)
6 or higher	-0.329***	-0.465***	0.003	-0.668***	-4.736***
	(0.001)	(0.003)	(0.004)	(0.004)	(0.028)
Ideal family size		0.093***		0.078***	0.553***
		(0.000)		(0.001)	(0.004)
Distance from ideal family size:					
-6			0.407***		
			(0.007)		
-5			0.445***		
			(0.005)		
-4			0.469***		
			(0.004)		
-3			0.474***		
			(0.003)		
-2			0.436***		
			(0.002)		
-1			0.329***		
			(0.001)		
1			0.050***		
			(0.002)		
2			0.005*		
			(0.002)		
3			-0.020***		
			(0.004)		
4			-0.024***		
			(0.006)		
5			-0.003		
			(0.015)		
6			-0.053**		
			(0.020)		
		✓	✓	✓	✓
Controls				✓	✓
Complete fertility sample	2116090	1031680	1031680	447861	447861

Notes: The outcome variable is an indicator for whether the mother had another child after child i. Columns 1 to 4 report the OLS results, while columns 5 the logit results, in terms of odds ratios. All regressions control for child gender, child birth order (truncated at 6), state fixed effects and urban/rural indicator. Controls include religion fixed effects, ideal family size and mother education in years. Column 2 controls linearly for ideal family size, while column 3 includes dummies for distance from ideal family size (omitted category is 0). Complete fertility sample only includes women who report being infertile or sterilized. * denotes 10% significance, ** denotes 5% significance, *** denotes 1% significance. Source: NFHS.

Table D.4: Fertility and Child Endowment (Child died)

Outcome variable: mother has an additional child	(1)	(2)
Child weight	-0.015*	0.932*
	(0.008)	(0.034)
Child is boy	-0.001	0.998
	(0.009)	(0.044)
Twin birth	-0.113***	0.599***
	(0.036)	(0.102)
Controls	✓	✓
Observations	10123	10123

Notes: The outcome variable is an indicator for whether the mother had another child after child i. Column 1 shows the OLS results, while column 2 the Logit results in terms of odds ratio. Controls include region fixed effects, urban/rural indicator, ideal family size, and child birth order. * denotes 10% significance, ** denotes 5% significance, *** denotes 1% significance. Source: C-NLSY79.

Table D.5: Fertility and Child Endowments (US Sample)

Outcome variable: mother exceeded desired fertility	(1)	(2)	(3)	(4)
Average size of children	0.916***	0.919***		
	(0.012)	(0.016)		
Endowment of child whose birth order coincides with desired fertility			0.643***	0.754**
			(0.060)	(0.091)
Education years mother		0.908***		0.804***
		(0.007)		(0.045)
Ideal family size		0.459***		1.039
		(0.009)		(0.136)
Controls	✓	✓	✓	✓
Mother controls		✓		✓
Observations	49455	31059	17048	8814

Notes: The outcome variable is an indicator for whether the mother exceeder her target fertility level. Coefficients are expressed in terms of odds ratios. Estimation sample only includes women who report being infertile or sterilized. Controls include state fixed effects and urban/rural indicator. Mother controls include desired fertility level, education and religion fixed effects. * denotes 10% significance, ** denotes 5% significance, *** denotes 1% significance. Source: NFHS.

Table D.6: Fertility and Child Endowments (Exceed Target Fertility)

E Data Appendix

E.1 Data for Figure C.2

This Appendix report the details of the test used to produce the results in Figure C.2.

Indonesia: The data for Indonesia comes from the last four waves of the Indonesian Family Life Survey Data (IFLS). The IFLS is an on-going longitudinal survey of Indonesian households. The sample is representative of about 83% of the Indonesian population and contains over 30,000. There are currently 5 rounds of the IFLS. The first wave of the IFLS (IFLS1) was conducted in 1993/94, while the fifth wave of the IFLS (IFLS-5) was fielded in 2014/15 (Frankenberg et al. (1995)). In each wave, all children between the ages of 7 and 24 were administered cognitive tests to assess their skills in the Indonesian language, in mathematics and their general cognitive level.[39] The tests were designed by members of the testing division of the Indonesian Ministry of Education, drawing on items the National Achievement Test (EBTANAS).

Mexico: The data for Mexico comes from three waves of the Mexican Life Family Survey (MxFLS). The MxFLS is a longitudinal, multi-thematic survey representative of the Mexican population at the national, urban, rural and regional level. Currently, the MxFLS contains information for a 10-year period, collected in three rounds: 2002, 2005-2006 and 2009-2012 Rubalcava & Teruel (2013). All children between five and twelve years old were tested using the Raven's coloured Progressive Matrices (J. C. Raven & Court (1938); J. Raven et al. (2003)).

US: The data for the US comes from the National Longitudinal Survey of Youth 1979 - Child and Young Adult (C-NSLY79). This is a longitudinal project that follows the biological children of the women in the NLSY-79 (Center for Human Resource Research (2004)). As of 2016, more than 10,000 children have been interviewed in at least one survey round. I use the Peabody Individual Achievement Test (PIAT) to measure child skills. This is a wide-range measure of academic achievement for children aged five and over. It is among the most widely used brief assessment of academic achievement with high test-retest reliability and concurrent validity.

Tanzania: The data for Tanzania comes from five rounds of the Uwezo initiative. Since 2010, the Uwezo initiative has undertaken large-scale household surveys in Kenya, mainland Tanzania and Uganda. In each wave, the literacy and numeracy abilities of children younger than 16 years of age were collected.

India: The Indian data comes from the India Human Development Survey (IHDS). The India Human Development Survey (IHDS) is a nationally representative, multi-topic panel survey. There are currently 2 rounds of the IHDS. The first wave of the was conducted in 2005, and the second one in 2011-12 (Desai et al. (2005); Desai & Vanneman (2015)). The survey includes a short reading, writing, and arithmetic

[39] Language skills were only measured in the second wave, while cognitive skills were measured from wave three onwards.

knowledge tests, which were administered to all children aged between 8 and 11 in the household. These tests were developed in collaboration with researchers from PRATHAM, India.

E.2 Fertility Data

The data used to test the third model prediction – that relates child endowments to househol fertility behaviou – comes from the National Family and Health Survey (NFHS). The NFHS is a repeated cross-sectional data set based on the Demographic and Health Survey (DHS). The NFHS surveys a representative sample of ever-married women aged between 15 to 49 across India. The analysis uses the 1992, 1998, 2005 and 2015 waves of the NFHS.

The data contain basic demographic characteristics of all survey mother as well as all of their children. The data allow to construct complete fertility histories for all survey respondents. The information of child endowment is collected as a maternal reported measure of child weight at birth. The survey question is:

> "*"When (NAME) was born, was he/she very large, larger than average, average, smaller than average, or very small?"*"

Endowments are therefore categorical and in the empirical analysis the excluded category is children whose endowments are reported to be "very small". The survey further includes a variety of information on maternal fertility including contraception use, child health and desired fertility (collected retrospectively). The information on desired fertility is used to construct an indicator for whether the mother exceeded her desired fertility level, which is used as an alternative outcome measure in the analysis.[40]

[40] Because this information is collected retrospectively, it may reflect mother's current attitudes towards her children based on factors observed since the child's birth (Rosenzweig & Wolpin (1993)). As such it may be a biased measure of parental fertility preferences. As a robustness check, I replicate the analysis using data from the C-NLSY79 which collects information of preferences at the beginning of the fertility spell and find similar results (see Table D.5).

	Full sample		Comple fertility sample	
	Mean	S.D.	Mean	S.D.
Urban	0.275	0.446	0.266	0.442
Maternal education in years	3.960	1.673	3.876	1.642
Mother is sterile	0.177	0.381	1.000	0.000
Ideal number of children	2.511	1.079	2.402	0.952
Number of children	2.595	1.857	3.170	1.622
Mother exceeded target fertility level	0.268	0.443	0.433	0.496
Birth order	2.439	1.657	2.854	1.503
Child is boy	0.520	0.500	0.596	0.491
Size of child (categorical 1-5)	2.978	0.739	2.906	0.757
Number of mothers	283284		50031	
Number of children	385006		69116	

Notes: This table presents the summary statistics for the National Family Health Survey sample. This is constructed pooling together the 1992, 1998, 2005 and 2015 waves. The 1992, 1998, 2005 and 2015 waves account for 12.54%, 8.55%, 13.15% and 65.76% of the sample. The first two columns report the summary statistics for the full sample, while the second two those for the sample with completed fertility (this includes only women who report having completed their fertility spell or being sterilized).

Table E.1: Summary Statistics - NFHS

F Experimental Procedures and Selected Survey Questions

F.1 Procedures

Figure F.1 describes the experimental procedures. First respondents were randomly assigned to whether in the experimental scenarios they saw two children of the same gender (two boys) or whether they saw one boy and one girl. In the first stage of the experiment, I elicited parental beliefs about the human capital production function. I then collected parental investment choices. Lastly, I collected data on actual investments made by parents in their children's education.

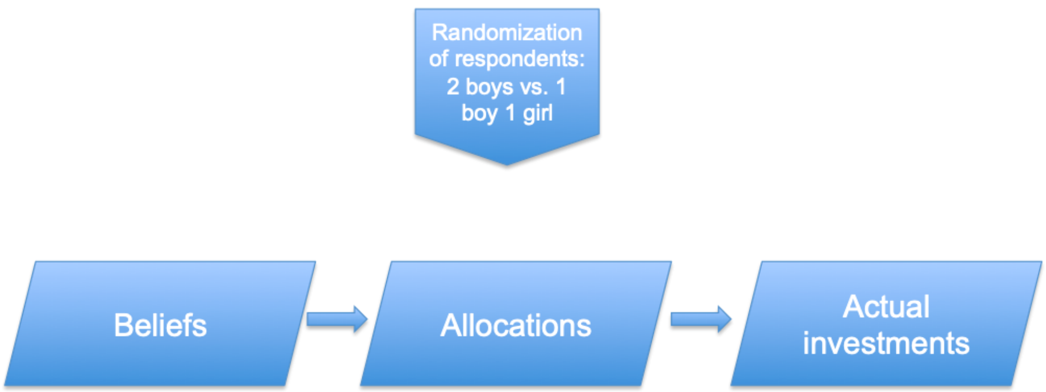


Figure F.1: How the experiment worked

F.2 Script for Beliefs

We are interested in your opinion about how important it is for parents to devote resources to help their children acquire new skills. For this purpose, we will ask you to imagine an typical family that lives in a basi/neighbourhood like your own. The family has two children, Abhisekh and Biswajeet, and makes decisions about how much money to spend on educational resources that help their children acquire new skills and progress in their education. We will show you different scenarios and ask you what you think the average monthly earnings of Abhisekh and Biswajeet will be at age 30 under each scenario. We will also ask you what grade you would expect Abhisekh and Biswajeet to reach in each scenario.

We know these questions are not easy to answer. Note that there is no right or wrong answer, we are just interested in what you personally think. Please try to consider each scenario carefully and tell us what you believe the outcome will be.

Instruction for Interviewer: show VISUAL AID 0 to the respondent. Explain that the ruler represents children schooling ability. Worse children in school are at the bottom of the ruler while best children are at the top. Probe respondent understanding of the ruler by asking: *"Show me by pointing with your finger where the worse performing student in the school would be on this ruler?"*, and *"Show me by pointing with your finger where an average performing student in the school would be on this ruler?"*. If respondent shows understanding continue with the survey, otherwise continue explaining [the visual aid] until respondent understands.

During primary school, the parents decide how much money to spend on educational resources that will help Abhisekh and Biswajeet acquire new skills and progress in their education (e.g. books, private tuition etc.). Remember that Abhisekh is among the top three students in his school and Biswajeet is among the bottom three students in his school.

Instruction for Interviewer: show VISUAL AID 1 to the respondent together with box A while you explain the scenario.

A) If the parents spend 10 RUPEES every month on educational resources to help Abhisekh with his education, and they spend 10 RUPEES every month on educational resources to help Biswajeet with his education:

- *How much do you think Abhisekh will earn on AVERAGE per MONTH at age 30?*
- *How much do you think Biswajeet will earn on AVERAGE per MONTH at age 30?*
- *What grade would you expect Abhisekh to achieve?*
- *What grade would you expect Biswajeet to achieve?*

Instruction for Interviewer: show VISUAL AID 1 to the respondent together with box B while you explain the scenario.

B) If the parents spend 10 RUPEES every month on educational resources to help Abhisekh with his education, and they spend 1000 RUPEES every month on educational resources to help Biswajeet with his education.

- *How much do you think Abhisekh will earn on AVERAGE per MONTH at age 30?*
- *How much do you think Biswajeet will earn on AVERAGE per MONTH at age 30?*
- *What grade would you expect Abhisekh to achieve?*
- *What grade would you expect Biswajeet to achieve?*

Instruction for Interviewer: show VISUAL AID 1 to the respondent together with box C while you explain the scenario.

C) If the parents spend 1000 RUPEES every month on educational resources to help Abhisekh with his education, and they spend 10 RUPEES every month on educational resources to help Biswajeet with his education.

- *How much do you think Abhisekh will earn on AVERAGE per MONTH at age 30?*
- *How much do you think Biswajeet will earn on AVERAGE per MONTH at age 30?*
- *What grade would you expect Abhisekh to achieve?*
- *What grade would you expect Biswajeet to achieve?*

Instruction for Interviewer: show VISUAL AID 1 to the respondent together with box D while you explain the scenario.

D) If the parents spend 1000 RUPEES every month on educational resources to help Abhisekh with his education, and they spend 1000 RUPEES every month on educational resources to help Biswajeet with his education.

- *How much do you think Abhisekh will earn on AVERAGE per MONTH at age 30?*
- *How much do you think Biswajeet will earn on AVERAGE per MONTH at age 30?*
- *What grade would you expect Abhisekh to achieve?*
- *What grade would you expect Biswajeet to achieve?*

F.3 Script for Allocation Choices

Now we will play a game with the goal of understanding how parents make decisions concerning their children, particularly how they make investments decision in their education. We understand that these decisions are often very complicated and we are just interested in finding out more about what factors are important in these decisions. There are no right or wrong answers here and there is no intention to make any judgement.

We will present you another family who lives in a basi/neighbourhood like your own. This family has two children and decides how to invest some money on each of their children's education. The family asks for your advice on how to spend this money. We will tell you different stories and in each of these stories we will ask you to advice this family on how to invest in their children's education reflecting your choices.

The game has several rounds that correspond to different stories. In each round I will give you some beans that represent Rupees that the family has decided to spend on their children's education. Each story will be characterized by:

1. *A total amount of Rupees to be spent. This is given by the total amount of beans.*
2. *An initial level of schooling ability of the two children.*
3. *An initial health status of the two children.*

After describing each story, I will ask you to advice the family on how to divide this money among their children (e.g. to pay for school fees, private tuition, schooling materials, etc.). Please use the beans and place them in the boxes to reflect your choices. For example if you wish to assign all the resources to "Child 1" you should put all the beans in the box labelled "Child 1". Please notice that you have to place all the beans that I give you into the boxes. Let's practice with an example!

Instruction for Interviewer: show VISUAL AID 4 to the respondent and hand 10 beans.
Trial 1: Probe respondent understanding by asking: *"Show me by placing the beans into the boxes how you would place the beans if you wished to spend all the rupees on Child 1."*
If responder shows understanding continue, otherwise continue explaining until respondent understands.
Trial 2: Probe respondent understanding by asking: *"Show me by placing the beans into the boxes how you would place the beans if you wished to spend the same amount on both children."*
If responder shows understanding continue, otherwise explaining again until respondent understands.
Once you are confident that the respondent understands collect all the beans and move on.

Please do not worry, there is no right or wrong answer and the intention is not to make any judgment. We understand that some of these questions might be hard, but please try to consider each scenario carefully. Before we start, do you have any question? Ok, let's start!

Imagine a typical family that lives in a village/neighbourhood like your own. The family has 2 primary school aged children, Pradeep and Sisir. At the beginning of the school year they decide how to spend some of their money on educational resources that will help their children to acquire new skills and progress in their education. The family asks for your advice on how to spend this money.

A) The family can spend 10 beans on their children's education. Pradeep and Sisir are both healthy children. At the beginning of the school year Pradeep is among the top three students in his school and Sisir is among the bottom three students in his school. I would like you to think about how this scenario and to place the beans into the boxes to reflect your choices.

B) The family can now spend only 3 beans on their children's education. Pradeep and Sisir are both healthy children. At the beginning of the school year Prandeep is among the top three students in his school and Sisir is among the bottom three students in his school.

C) The family can spend 10 beans on their children's education. Pradeep and Sisir are both healthy children. At the beginning of the school year Pradeep is among the top three students in his school and Sisir is an average student in his school.

D) The family can now spend only 3 beans on their children's education. Pradeep and Sisir are both healthy children. At the beginning of the school year Pradeep is among the top three students in his school and Sisir is an average student in his school.