The Role of Gender, Birth Order, and Ability in Intra-household Educational Inequality: Evidence from Benin*

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Abstract

This paper explores how gender, birth order, and innate ability affect educational disparities among children within households. Using both a reduced-form approach and a structural model of household educational resource allocation, it identifies the contributions of gender and birth order to intra-household educational inequality. In Benin, significant disparities are found in households with non-educated heads and mixed-gender children, with 70% of the inequality attributed to gender and birth order. In contrast, households led by college-educated heads show 24% gender effects and 9% birth order effects. Additionally, college-educated parents exhibit less overall educational inequality among their children. Policy counterfactuals assess the impact of (1) education vouchers, (2) compulsory education, and (3) targeted educational cost reduction for non-educated parents. All three policies reduced the effects of gender and birth order on inequality. Compulsory education reduced overall average inequality, while targeted educational cost reduction completely eliminated gender and birth order effects. This research underscores the complex factors driving intra-household educational inequalities and suggests effective policy measures.

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1 Introduction

The trade-off between the number of children one chooses to have and the quality of those children has been a subject of extensive research. This exploration began with the seminal contributions of De Tray (1970) and Becker and Lewis (1973). The quantity-quality trade-off model delves into how changes in the quantity of children can impact their average quality. Numerous empirical studies have provided support for this model in various contexts, consistently revealing a negative relationship between the number of children, often used as an empirical measure of quantity, and the educational attainment of those children, typically used as an empirical measure of quality. These findings align with the predictions put forth by the theoretical framework presented by Becker and Lewis (1973) and have been substantiated by research such as Montgomery (1995) and Li et al. (2008). The current state of the literature on fertility choices (Conley and Glauber (2006), Maralani (2008), Li et al. (2008), Weng et al. (2019)) states that rich and educated families tend to have fewer children while allocating greater investments in the education of those children, in comparison to less affluent and less educated families. In other words, the average level of education among children varies across different families, influenced by endogenous factors such as family size and exogenous factors like the socio-economic background of the parents.

When we extend the analysis beyond the choice of the aggregate quality of children to how it is distributed among children, we observe that, not only does the average change across households, but so does the variance of quality. In addition, the variance is most likely non-zero for a majority of households when there are budget constraints and no compulsory education laws. This presumption of a non-zero variance is justified by evidence of the influence of factors such as gender, birth order and innate ability on education attainment of children. The educational outcomes of children are strongly influenced by their individual characteristics, leading to disparities in the amount of education they receive. Several studies have shed light on these disparities, with findings indicating that girls tend to receive less education due to factors such as gender bias or gender preference (as documented by Biswas (2000) and Ota and Moffatt (2007)). Additionally, birth order can play a role in the educational opportunities afforded to children, with elder siblings benefiting or facing disadvantages, as observed in studies like Ota and Moffatt (2007), Weng et al. (2019), Fergusson et al. (2006), De Haan (2010), Moshoeshoe et al. (2016), and Esposito et al. (2020). Furthermore, children with higher abilities are more likely to receive increased educational opportunities and education attainment, as suggested by the research of Becker and Tomes (1976), Dizon-Ross (2019), and Giannola (2023). However, there exists a notable gap in the research landscape, as there is a scarcity of studies that comprehensively analyze all these various sources of disparities within the same analytical framework. Such a framework, capable of simultaneously examining gender-based differences, birth order effects, and the impact of individual abilities on educational inequality within households, holds the potential for interesting counterfactual and education policies analyses. Specifically, it enables us to explore how these factors interact with one another to shape inequality. Furthermore, this comprehensive approach is crucial for estimating the proportion of inequality attributable to gender and birth order and the portion caused by ability-based resource allocation within households. The former allows us to design education policies which target inequality due to gender or birth order disadvantages.

In this paper, I use a reduced form approach and suggest a structural model to analyze the intra-household differences in children's education. Firstly, through a reduced form analysis, I break down the total observed disparities into gender effects, birth order effects, and an unexplained residual. Secondly, the structural model allows us to assess the extra intelligence needed by a daughter (or firstborn) to match the educational opportunities of a son (or second-born). Lastly, using the structural model, we can examine how differences in education of children within a family change with a cost reduction policy compared to an education voucher or compulsory education policy.

I examine this question within the empirical context of Benin in West Africa. Benin is an ideal location for this study for three main reasons. First, even though there is a law stipulating that everybody must finish at least primary school, it's not always followed by parents or enforced by the government. Second, there are big differences in how much education individuals in the same household get. Also, these differences can be very different from one family to another. Lastly, there is evidence that girls and firstborns often don't get the same education opportunities as others. For this exercise, I focused on households where there were only two adult children still residing with their parents[1]. Among those households there is difference in how much education resources they have to distribute and the education attainment of the head of household. Taking that into account, I applied my method to households with different characteristics separately.

My analysis uncovered three important findings. First, when it comes to educating daughters compared to their brothers within a household with a non-educated head of household, large part (70%) of the differences in the education of brothers and sisters is due to gender and birth order effects rather than variations in abilities. That number is 33% among college educated parents. However, when examining the education of firstborns compared to their siblings of the same gender, more than two-third (70% for female and 80% for male) of the disparities are attributed to differences in abilities. These results suggest that in some

[1] The extension to households with more than 2 children is straightforward. All the estimates and analysis in the paper are also done after including households with 3 children and the results are presented in the appendix of the paper.

households gender disadvantage reduces disparities in children's education through the reduction of the extent to which the talent of a child affects their education. This implies that removing/reducing gender and birth order effect will not systematically reduce inequality for all households. It will increase the amount of disparities in some households.

Second, When we reduce education costs for firstborn children and daughters, we can decrease the differences in education within certain families. This is especially true in families where the firstborn children and daughters have lower abilities compared to their siblings or where parents don't really take the children's abilities into consideration when making decisions about education. However, if the firstborn children and daughters are actually more capable than their siblings and parents do consider their abilities, a policy that eases the financial burden of schooling for them might unintentionally increase educational differences within the family. This brings up a dilemma about finding the right balance between giving everyone equal educational opportunities, regardless of factors like gender, birth order, and ability, and ensuring that children with similar abilities get the same opportunities, regardless of gender and birth order. In the latter case we are allowing for rewarding high abilities but not for penalizing gender and birth order.

In terms of policy changes, it seems more implementable to aim for the latter option. That means focusing on policies that increase the net return from education for firstborn children and daughters either through schooling cost reduction or reduction of salary gap between male and female. These policies will help decrease the impact of gender and birth order on educational differences. On the other hand, it's trickier to implement a policy that reduces how much parents consider a child's abilities in distributing the few resources that they have, when facing financial challenges. Especially given that it is more costly to give high level formal education to a low ability child, and that there are other more suitable alternatives such as apprenticeship.

Third, I conduct the following 3 education policies counterfactual among non-educated parents and analyze how each of them affect gender and birth order effects and overall inequality. The first policy (1) of the form of an education voucher reduces gender and birth effects, but did not change overall average inequality in the sample. The second policy (2) of the form of compulsory education reduces both the effects of gender and birth order and the average inequality in the sample. The third policy (3) of the form of targeted education cost reduction by construction eliminates completely the effects of gender and birth order but did not change the average inequality in the sample.

The subsequent sections of this paper are structured as follows. In Section 2, I present the literature review along with the specific contributions of this paper. Section 3 offers an overview of the data used for this study, while Section 4 presents key empirical observations and stylized facts derived from the data description. Section 5 is dedicated for the model's setup, outlining the identification strategy for key parameters, and describing the inference and estimation procedures employed in this study. Lastly, in Section 6, I present counterfactual analysis to further explore the implications of my findings. Section 7 presents a robustness analysis of the key parameters of interest, and Section 8 concludes the paper.

2 Literature Review

This paper contributes to the extensive literature on fertility choice models and the quantity-quality trade-off faced by households within a country. Early developed theoretical models (DeTray (1970), Becker and Lewis (1973)) predicts that quantity and quality of children are negatively related due to the observation that the shadow price of quantity is influenced by quality, and vice versa. More specially, they have shown that a reduction in the quantity of children results in a decrease in the shadow price of quality. Consequently, this decline in the shadow price of quality leads to an increase in the overall quality of the children. The current state of the literature on fertility choices (Montgomery (1995), Conley and Glauber (2006), Maralani (2008), Li et al. (2008), Weng et al. (2019)) states that rich and educated families tend to have fewer children while allocating greater investments in the education of those children, in comparison to less affluent and less educated families. This trend reflects a significant pattern where socio-economic factors play a crucial role in shaping fertility decisions and educational investments within households. However, some studies still found a positive or no correlation between fertility and education of children either for rural or old households (Montgomery (1995), Black et al. (2005), Maralani (2008)). This is often explained by the lack of contraception methods and poor public education systems. This paper contributes to that strand of the literature by offering two key contributions. Firstly, it empirically demonstrates the existence of a quantity-quality trade-off within the context of Benin. Second, it builds on this result to relax the assumption of equal education for children in the same household.

This paper also contributes to the literature on the within-household schooling decision, particularly factors influencing parents' distribution decision of education resources among siblings. One key determinant of these distribution decisions is the gender or gender composition of households. Previous research has shown that daughters are less likely to receive education or have lower educational attainment on average. Studies have shown that, while the presence of elder sisters tends to increase the likelihood of schooling, the presence of younger brothers may decrease it (Biswas (2000), Ota and Moffatt (2007), Ombati and Ombati (2012), Osadan and Burrage (2014), Psaki et al. (2018)). Another influential factor is the birth order of children, with mixed findings in previous studies. Some papers suggest a positive effect of birth order on children's education (Ota and Moffatt (2007), Weng et al. (2019)), while others have shown that later-born children have lower educational attainment (Fergusson et al. (2006), De Haan (2010), Moshoeshoe et al. (2016), Esposito et al. (2020)). Finally, a child's innate ability or talent plays a role in parental distribution decisions. Studies have demonstrated that parents invest more in the human capital of endowed children and allocate more nonhuman capital to less endowed children (Becker and Tomes (1976), Dizon-Ross (2019), Giannola (2023)). When parents are compelled to invest in the nonhuman capital of low-ability children, this leads to an inefficient equilibrium, where the investment in the human capital of high-ability children is not optimized (Nerlove et al. (1984)). This paper adds to this existing literature in two significant ways. Firstly, it examines a context where parents are not constrained to compensate lower ability children by investing in their nonhuman capital but, instead, rely on family taxes (Wantchekon et al. (2015)). Secondly, this paper develops a household resources distribution structural model that allows for a more flexible analysis of the distribution of education resources within the household. In this model, the assumption of equal distribution is relaxed, enabling a detailed exploration of the interactions between gender and, birth order disadvantages, and the innate abilities of individual children in influencing parental distribution decisions.

This paper also contributes to the literature on educational Kuznets curve theory (Thomas et al. (2003), Londoño (1990) and Ram (1990)). Previous studies have analyze the relationship between mean and variance of education using across countries data or within country across time data. This paper contributes to that literature by analyzing the relationship between mean and variance of education using within country across households data. Specifically, it shows that in Benin as we move from zero to maximum level of average education, the variance first increases and then start decreasing around an average of 7 years of education.

Finally, this paper contributes to the literature on within household inequality in children's human capital (Giannola (2023)). Giannola (2023) has shown in the context of India that observed inequality within households is partly explained by parents investing more in the human capital of high-achieving children, especially when they are financially constrained. This behavior stems from the fact that parents are not particularly averse to inequality and tend to reinforce the gap in learning created by innate ability rather than correct it. This paper contributes to that literature by first building upon the result that parents unequally invest in the human capital of high-achieving children in contexts where the education system is better tailored to serve high-achieving students. Second, this paper interacts with that result and examines how it relates to other sources of unequal distribution, such as gender and birth order.

3 Data Description and Definition of Key Variables

In this section, I present the data used to analyze the question of interest in this paper. The context of Benin is particularly compelling for analyzing the interaction between gender disadvantage, birth order advantage, and innate ability in shaping within household inequality for three reasons. First, there are a lot of disparities in education attainment within households due to the lack of compulsory education law coupled with financial constraints and the availability of outside options other than formal education such as child labor within the households and apprenticeship. Second, there is factual evidence of gender and birth order disadvantages. Lastly, there is observational evidence that despite the prevalence of gender disadvantages in the population, daughters in some households get higher education than their brothers.

3.1 Sample and Data

The 2013 Population and Habitation Census data of Benin; used in this paper; offers a comprehensive insights into households and their members living in the country during that year. Conducted by the National Bureau of Statistics of Benin, this census provides data at both the household and individual levels. For the purpose of this paper, the focus is directed towards individuals who identify themselves as the children of household heads, enabling to get information on parental [2] and sibling characteristics for a sub-sample of siblings. To be specific, the variable "Number of children" represents the observed number of children within each household [3]. For the primary analysis, only households with children aged between 25 and 40 years are included. This age range is chosen to ensure that the children have either completed their education or nearly achieved complete educational attainment.

The inequality analysis focuses on households with at least 2 such children falling within the specified age range and at least one child with some educational attainment. This specific sample selection is motivated by the desire to examine the consequences of providing equal education to all children, as opposed to the alternative of not educating any children. The resulting sample comprises approximately $90,000$ individuals and $32,000$ households, serving as the basis for further investigation. The sample description is presented in Figure 1.

1. **Sample 1:** households with at least 2 children between 25 and 40 years old. ($\approx$ 51,600 households)

[2] Parents here refers to one of the parents, either the mother or the father. This because it is not possible to have both for household with single parents and to identify the biological mother for polygamous households.

[3] It does not include children who moved out of the family house before the census.

2. **Sample 2:** households with at least one educated child between 25 and 40 years old.($\approx$ 32,800 households)

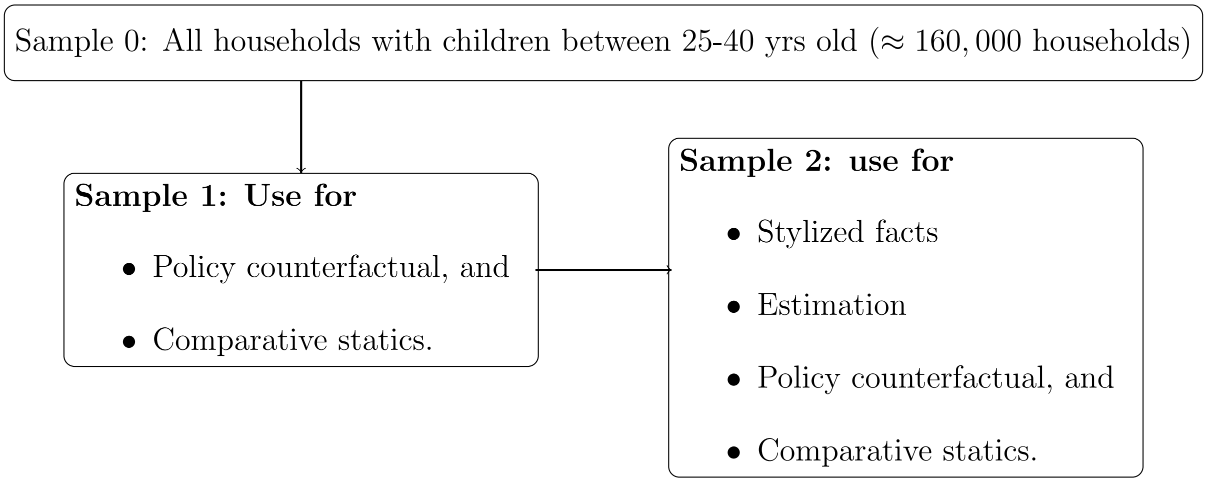


Figure 1: Sample Description

3.2 Key variables and measurement

The data set contains several key variables used in this paper, including gender, age, religion, area of residence, family size, household wealth index, and educational attainment of individuals, as well as their parents' and a subset of their siblings' variables. Apart from these variables, I also created measures for within household inequality, within household average years of education, and gender composition of children within a household. A description of each variable and their measurement is as follows:

Inequality: It refers to inequality in the education attainment of children within a given household. It is measured by the within household standard deviation and range of children's education attainment. These two measures are used interchangeably throughout this paper.

High school graduate head of households/parents: It refers to head of households with at least 13 years of education. The education of the head of household is also used to describe the household. In other words, households with head of household with at least 13 years of education are referred to as high school graduate households.

Number of children: It is the total number of people who identify as children of a the head of household. This variable is denoted by N_c.

Within household average years of education: It is the average education of children between 25 and 40 years for a given household. It serves as a metric for accessing the average quality of children within the household. A related variable is the **Within household total years of education**, which is the simple sum of children's years of education. It is used as a proxy for the household's total investment in education. The within household total and average years of education of children are denoted by q_T and $\bar{q}$ respectively.

3.3 Descriptive statistics

Table 2 displays the descriptive statistics for the key variables. Among the offspring, 38% are female, and their average education level is 8 years, with 80% having completed at least one year of education. Additionally, 40% of the heads of households have at least one year of education. About 80% of children without any schooling have parents who also lack formal education, whereas this percentage decreases to 50% for children with schooling. Conversely, approximately 31% of parents without schooling have children who likewise lack schooling, compared to only ≈ 10% for parents with schooling (See Figure 2). These statistics provide suggestive evidence of both inter-generational educational mobility [4] and inter-generational educational persistence[5].

4 Empirical Evidence

4.1 Within and Between Household Inequalities

In this section, I provide empirical evidence using a variance decomposition analysis to calculate the average within-household variation in education and compared that to the overall variation in education in the sample. Through this analysis, I seek to understand how much of the educational disparities in the sample can be attributed to differences within households. Furthermore, I examine how within and between household variances in education are related. Let $q_h = (q_{h,1}, q_{h,2}, \ldots, q_{h,N_c})$ be the vector of children's education attainment in household h, and let $q = (q_1, \ldots, q_n)$ be the education attainment of children in the sample.

$$Var(q) = Var_h E[q|h] + E_h Var(q|h).$$

[4] Children are more educated than their parents

[5] Children's education is correlated with their parents' education.

The variance of q is the sum of within and between household variation in q.

$$\hat{E}_h \hat{Var}(q|h) = \hat{E}_h \hat{Var}(q_h) = 22.63 \text{ and } \hat{Var}(q) = 33.66$$

This indicates that 67% of the variation in q arises from variation within households. Furthermore, in the absence of within-household inequality, the between-household variance in children's education attainment is 20.9. However, in the presence of within-household inequality, the between-household variance in children's education attainment decreases to 11.2. These statistics suggest that, on average, households with some degree of within-household inequality exhibit lower between-household inequality compared to households with no within-household inequality. In conclusion, the analysis highlights on one hand the substantial contribution of within-household inequality to the overall inequality in education attainment. On the other hand, no within household variation in education of children is associated with higher between households variance. This suggests that households with greater disparities in education attainment among their members tend to exhibit lower disparities in education attainment when compared to other households.

4.2 Within household inequality in children's education

This section focuses on the extent of variation in within household inequality across households. I present evidence of differences in the magnitude of within household inequality across households. Understanding these differences can provide valuable insights into the factors that contribute to within household inequality and the potential mechanisms that can be employed to reduce it.

Figure 3 depicts the empirical distribution of the within household range and standard deviation of the education attainment of children. This figure provides compelling evidence of the variation in within household inequality in the educational attainment of children. Specifically, the data reveals that the magnitude of inequality varies across households, with some household having all of their children with the same education attainment while some have at least a child with some college education and at least a child with no education. These findings highlight the importance of considering household-level dynamics when addressing educational inequality and suggest that interventions aimed at reducing disparities in education must be tailored to the unique circumstances of each household. The inequality is present even within gender, although in lower magnitude. About 40% (resp. 60%) of household has some level of inequality among daughters (resp. among sons).

The within household variance of children's education is non-zero on average for all level of parents' education and wealth index (see Figure 4). However, it appears that within household variance of children's education decreases with parents' education level and wealth index. We observe a first order stochastic dominance between the empirical cdf of within household inequality in children's education of college educated (resp. high wealth index) and non-college educated (resp. low wealth index) parents.

At the household level, a negative association emerges between the maximum education attainment within a household and the proportion of children within that household who have achieved this maximum education level. We can have an evidence of this through an OLS regression of the within household maximum years of education of children on the proportion of children with education attainment equal to that maximum.

$$q_h^{\max} = \beta_0 + \beta_1 \frac{1}{N_c} \sum_{i=1}^{N_c} 1\{q_i = q_h^{\max}\} + \gamma' X_h + \varepsilon_h, \tag{1}$$

where X_h include number of children, HWI, area of residence, religion, gender composition of children, and head of household' s education. The estimation results in column (3)- (4) of Table 3 indicates that, on average, households with a 0.01 higher proportion of children attaining the maximum years of education within the household tend to have around 2.6 years lower maximum education levels for children within the household. Additionally, an OLS regression of the within household maximum years of education of children on the within household standard deviation of children's education indicates that households characterized by higher levels of educational inequality demonstrate, on average, higher within-household maximum education attainment (see column (1)- (2) of Table 3). These findings suggest a trade-off involved in households' education decision. The same argument as Becker and Lewis (1973) applies here, i.e. an increase in quality [6] is more expensive if there are more children with that quality. An increase in quantity[7] is more expensive if children are of high quality. This trade-off is a direct effect of the limited education resources available to households. In conclusion, due to financial constraints within the household, parents are facing a trade-off between reducing inequality within the household or reducing inequality between them and other households.

4.3 Parents' education, average within household education of children, and inequality

The level of education attained by the head of a household has been found to be a significant factor in determining the level of inequality in children's education attainment within that

[6] Here quality refer to the within household maximum years of education of children

[7] Quantity refers to the number of children with the within household maximum years of education of children

household. In particular, an increase in the head of household's education level is associated with a decrease in inequality. However, it remains unclear whether this is a direct result of more educated parents' aversion for inequality or an indirect result of their preference for education. To shed light on this issue, this section will investigate the factors that contribute to the observed negative correlation between parents' educational attainment and within household inequality.

In addition to having lower level of inequality, households with more educated head of household also tend to have higher average years of education for their children (See Panel (a) of Figure 6). This observation is particularly interesting given the hump-shaped relationship between inequality and average education of children (See Panel (b) of Figure 6). This inverted U-shaped relationship between average and standard deviation of children's education is consistent with the educational Kuznets curve theory (Thomas et al. (2003)). According to the Kuznets curve theory with education distribution, as we move from zero to maximum level of education, the variance first increases and then decreases. This is empirically shown for a set of developing countries in Londoño (1990) and Ram (1990). To investigate this relationship further, I estimate an OLS regression model of within inequality on average education of children, and parents' level of education, with a quadratic interaction between between this two variables.

$$Inequality_h = \alpha + \beta_1 \bar{q}_h + \beta_2 \bar{q}_h^2 \beta_3 hh\_Educ_h + \beta_4 \bar{q}_h hh\_Educ_h + \beta_5 \bar{q}_h^2 hh\_Educ_h + \gamma' X_h + \varepsilon_h, \quad (2)$$

where X_h include number of children, HWI, area of residence, religion and gender composition. The estimation results in column (5)- (7) of Table 3 suggest that the negative dependence between parents' education and within inequality is a result of both variable being correlated with the within household average education of children. In particular, the positive correlation between parents' education and the within household average education of children combined with the hump shaped relation between within household inequality and the within household average education of children is translated into the observed spurious negative relationship between parents' education and within household inequality.

4.4 Observed and unobserved sources of inequality

In the preceding sections, I have presented evidence at the household level, revealing that various factors contribute to the heterogeneity observed in the level of educational inequality across households. Notably, factors such as budget constraints, total investment in education, and the number of children play significant roles. By identifying and understanding these sources of heterogeneity, we gain valuable insights into the underlying mechanisms driving educational inequalities at the household level. In this section, the focus is on exploring the observed characteristics of children who received less education compared to their siblings. The examination of these characteristics is essential for developing effective strategies to address inequality and promote equality of opportunity for all children. Figure 8 graphs the average years of education based on the gender of children and the gender composition of households. To ensure accurate comparisons, the graph holds the within household average education of children constant. In the first panel, the analysis centers around households that are only able to finance primary school education for all their children. In the second panel, households that can only afford to provide education up to junior high school level are considered. The figure reveals some interesting trends in educational attainment among different gender composition households. Specifically, girls from only-daughter households, on average, have the same level of education as the household average, while boys from only-son households have similar education levels as well. However, in both-gender households, girls' average education is lower than the household average, whereas boys' average education is higher. These findings suggest that there is discrimination against daughters when it comes to the allocation of education quotas, when the alternative of giving more to a son is available.

Figure 9 allows similar analysis in terms of children's birth order after controlling for number of children, and within household average years of education of children. The figure provides insight into the average years of education of first and second children from two children households. In panel (a) of Figure 9, the plot is for households that can afford to educate all their children up to primary education, and for households that can afford to educate all their children up to junior HS education is in panel (b). The figure demonstrates that the average years of education for the firstborn children is below the household average for both type of households, whereas the average years of education of the second-born children is above the household average. This monotonic increase in education by birth order applies to any family size (See Appendix). The findings of Figure 9 suggest that there is disadvantage in birth order regarding the allocation of education quotas.

In summary, a child's gender, the gender and their siblings and their birth order are key determinants of the years of education they will receive. Despite taking into account observable household and children characteristics, a significant amount of variation in inequality across households remains unexplained, as evidenced by the R^2 value obtained from the regression of within household standard deviation of children's education on those observable household and children characteristics (See the last two columns of Table 3). In addition, despite the presence of gender disadvantage against daughters, it appears that in some households, daughters receive higher education than their brothers (see Figure 10). I hypothesize that the unexplained difference in inequality can be attributed to the variance in children's innate abilities, which differs across households. In other words, the fact that some daughters receive higher education compared to their brothers despite gender disadvantages can be attributed to high ability draws by these girls. This is a significant aspect of the household's education distribution model, which I present in the next section.

4.5 Decomposition of Within Household Inequality

In the previous section, I have presented some empirical evidence about the observed characteristics of children which explain the within household inequality in their education. Additionally, it was demonstrated that a portion of this inequality can be attributed to the children's unobserved abilities (or unobserved factors). In this section, I will provide a decomposition of the average within households inequality, categorizing it into components associated with gender disparity, birth order effects, and variations in children's abilities. Such decomposition is conducted across various average educational levels within households on one hand and parents' education level on the other hand. I used a household fixed-effect regression approach to achieve this breakdown.

Regression with Household Fixed Effects

To decompose the average within household inequality into components categorized as gender and birth order effects and unobserved differences, I consider the following regressions:

$$Educ_{i,h} = \beta_1 Female_{i,h} + \beta_2 Firstborn_{i,h} + \beta_3 Female_{i,h} \times Firstborn_{i,h} + \nu_h + \varepsilon_{i,h} \qquad (3)$$

$$Educ_{i,h} = \beta_1 Firstborn_{i,h} + \nu_h + \varepsilon_{i,h} \qquad (4)$$

where $Educ_{i,h}$ is the years of education of child i in household h, $Female_{i,h}$ is a gender indicator variable equals to 1 if child i in household h is a daughter, $Firstborn_{i,h}$ is a birth order indicator variable equals to 1 if child i in household h is a firstborn, and ν_h is the household fixed effect. Equation 3 is for households with both sons and daughters, while equation 4 is for households with either only sons or only daughters. The estimates from equation 3 and 4 are presented in Table 4 by average education of children and in Table 5 by parents' education. The results suggest, on one hand, that about 63% of the observed within household inequality in children's education is due to gender and birth order disadvantages for households with both son and daughter. On the other hand, for households with only daughters or only sons, about 33% of the observed inequality is due to birth order disadvantages. This change is due to the fact that part of the unobserved sources of inequality is muted by gender disadvantage. In other words, gender disadvantage not only exacerbates overall inequality but also diminishes the inequality driven by differences in unobserved ability.

For the primary analysis, which focuses on households with just two adult children living at home, the reliability of the estimates shown in Tables 4 and 5 may be compromised. This unreliability stems from the incidental parameter problem, a consequence of having only two data points per household for the fixed effect regressions. To validate the initial findings, I use the following alternative regression for a more robust examination.

$$\Delta_{daughter-son} Educ_h = \beta_0 + \beta_1 Firstborn\_daughter_h + \varepsilon_h, \tag{5}$$

where $\Delta_{daughter-son} Educ_h$ is the average difference in the education of sons and daughters in household h, $Firstborn\_daughter_h$ is an indicator variable equals to 1 if the firstborn in household h is a daughter. The estimates are summarized in Figure 12. Figure 12 illustrates the mean disparity in educational attainment between daughters and sons, with households having a firstborn male and female shown in red and blue, respectively. These measurements are provided across various average educational levels of the children in the panel a) and across education of the head of household in panel b), facilitating a decomposition for each average education and parents' education level as follows:

$$\text{In blue: the average effect of gender } + \text{ the average effect of birth order } (\beta_0 + \beta_1), \text{ and} \tag{6}$$

$$\text{In red: the average effect of gender } - \text{ the average effect of birth order } (\beta_0), \tag{7}$$

Let $q_h = (q_{1,h}, q_{2,h})$, and $Range_h = max(q_h) - min(q_h) = |q_{1,h} - q_{2,h}|$

Claim 1: [8]

$$E[\text{Range}|\text{household has a firstborn daughter}] \geq |\beta_0 + \beta_1| \tag{8}$$

From equation 8,

$$\text{Effect of unobserved factors} = E[\text{Range}|\text{household has a firstborn daughter}] - |\beta_0 + \beta_1| \tag{9}$$

Average Inequality Decomposition

By combining equations 6 and 7, we can derive the average impact of gender and birth order disadvantages on the average within households inequality at each level of the children's average educational attainment and parents' education. This integration enables us to break down the average inequality found within households into the three factors illustrated in Figure 13. This figure showcases how the average inequality is divided among gender disadvantage, birth order disadvantage, and differences in unobserved factors. It re-

[8] The proof is presented in Appendix

veals that gender disadvantage is the predominant factor contributing to inequality. As the average educational level of children increases, the influence of unobserved ability differences becomes more significant, while the impact of birth order diminishes. Similarly, as parents' education level increases, total inequality is smaller on average, and the share of birth order disadvantage reduces; but the share of gender disadvantage does not change significantly. This indicates not only the presence of variability in the degree of inequality across different levels of children's average education and parents' education but also in the way it is broken down.

Extensive versus Intensive margin inequality Decomposition

It is relevant to analysis how within household inequality in education is decomposed for the extensive margin compared to the intensive margin. To analyze that, I run the previous fixed effect regression in equations 3 and 4 for households with only educated children— for the intensive margin analysis—, and the following regression for households with at least one non-educated child— for the extensive margin analysis.

$$1\{Educ_{i,h} > 0\} = \beta_1 Female_{i,h} + \beta_2 Firstborn_{i,h} + \beta_3 Female_{i,h} \times Firstborn_{i,h} + \nu_h + \varepsilon_{i,h} \quad (10)$$

The estimates are presented in Table 6, and the decomposition of inequality at extensive and intensive margins is presented in Figure 14. The numbers indicate that parents' education is negatively related to inequality in children's education mostly at the extensive margin. In particular, panel a) of Figure 14 shows the proportion of households with a non-educated child by parents' education. That number is the highest among non-educated parents ($\approx$ 50%) and close to 0 ($\approx$ 3%) among college educated parents. There is also a substantial heterogeneity in the decomposition of inequality at the extensive margin. Specifically, for most of non-educated households with a non-educated child, the non-educated child is either a daughter or a firstborn. This is not true among college educated parents.

5 The Model

5.1 Setup

The model I have developed considers children as investment goods rather than mere consumption goods. In other words, the number of children does not enter parents' utility function directly like in Becker and Lewis (1973). Parents' choices consist of 2 distinct stages. In the first stage, households make decisions regarding the number of children, denoted as

N_c, and observe their abilities [which are unobserved to the econometricien], represented by the vector $\omega = (\omega_1, \ldots, \omega_{N_c})$. They then choose the aggregate total years of education attainment, denoted as q_T, for these N_c children. This leads to a within-household average years of education of children, represented as $\bar{q} = \frac{1}{N_c} q_T$. This initial stage can be viewed as choices derived from solving a fertility choice model, resembling the one described in Becker and Tomes (1976), with the distinction that each child is not assumed to receive $\bar{q}$ years of education. In other words, the decisions made in the first stage are based on the quantity-quality trade-off theory. This leads to different choices on average for parents with different level of education. In addition to allowing an influence of parents' education on the quantity of children and resources devoted to their schooling, I account for an unobserved heterogeneity that reflects parents' constraint to having a child without education. This unobserved constraint parameter dictates the percentage of uneducated children within the family.

In the second stage of their decision, households shift their focus to deciding on the distribution of q_T. This decision is dictated by the constraint parameter combines with children's observed and unobserved characteristics. Specifically, each household is characterized by a type ν_h (their constraint of having uneducated children). Given ν_h, a household chooses the proportion of N_c that receives some education, and distributes q_T among those children taking into consideration their gender, birth order and innate ability. The decision of parents is to choose the distribution $(q_1, \ldots q_{N_c})$ of q_T, which maximizes the household's utility function.

$$\max_{q_i} U(q, \theta) \tag{11}$$

$$\text{subject to } \sum q_i \leq q_T, \; q_i > 0, \; q_i \leq q_{\max}$$

$U(.)$ is increasing and concave, and $q_{\max}$ is the maximum years of education a child can receive. θ is the vector of parameters described in the next section. The model mainly analyzes decisions in the second stage, taking choices in the first stage as exogeneously given.

5.2 Functional form of households' utility [for households with 2 adult children]

Drawing upon the empirical evidence presented in Section 4, I have adopted the following generalized utilitarian social welfare function with concave utility function for each child to represent parents' utility function. This form reflects the preferences and decision-making processes observed in the data and serves as a crucial component in the model. Let $q_h = (q_{1,h}, \ldots, q_{N_c,h})$ be the distribution of $q_{T,h}$ in household h. The utility function for households with 2 children has the following expression[9]:

$$U(q_h) = \nu_h \Big[\sum_{i=1}^{N_{c_h}} a_{i,h}.(q_{i,h})^{\delta_{i,h}^{low}} - \alpha_i^{low} q_{i,h} \Big] + (1-\nu_h) \Big\{ \sum_{i=1}^{N_{c_h}} \Big[e_{i,h}.\big(a_{i,h}.(q_i)^{\delta_{i,h}^{high}} - \alpha_i^{high} q_{i,h}\big) \Big] \Big\}, \quad (12)$$

where,

- $a_{i,h} = \frac{\omega_{i,h}}{\sum_{j=1}^{N_{c_h}} \omega_{j,h}} \sim G(.)$ captures parents' preference for child i relative to other children in household h based on their unobserved ability draws,
- $\nu_h \sim Bernoulli(p_h)$, is parents' constraint for having an uneducated child. For parents with 2 children, the unobserved type falls into two categories: high or low. With 'high' ($\nu_h = 0$) indicating high constraint and resulting into having an uneducated child, and 'low' ($\nu_h = 1$) indicating low constraint resulting into an absence of constraint to having an uneducated child.
- $e_{i,h} = 1\{a_{i,h}.(q_T)^{\delta_{i,h}^{high}} - \alpha_i^{high} q_T > a_{j,h}.(q_T)^{\delta_{j,h}^{high}} - \alpha_j^{high} q_T\}$, $e_{j,h} = 1 - e_{i,h}$. $e_{i,h}$ and $e_{j,h}$ are indicator of whether not children i and j in household h have some education.
- $\delta_{i,h}^{low} = \delta(gender_{i,h}, gender\_comp_h) = \gamma - \theta_1^{low} Female_{i,h}(1 - Female_{j,h})$.
- $\delta_{i,h}^{high} = \gamma - \theta_1^{high} Female_{i,h}(1 - Female_{j,h})$. $\delta_{i,h}$ is the marginal benefit from giving a year of education to child i in household h.
- α_i^{low}, and α_i^{high} are the costs (financial and opportunity costs) of giving a year of education to i^{th} child at the extensive and intensive margin respectively.
- $q_{i,h}$ is the total years of education of child i in household h.

We allow θ_1^{high} to be function of daughter's birth order,

$$\theta_1^{high} = \theta_1^{ds,high} 1\{gender\_comp = b^{d,s}\} + \theta_1^{sd,high} 1\{gender\_comp = b^{s,d}\}$$

with, $b^{d,s} = Female_1.(1 - Female_2)$, $b^{s,d} = (1 - Female_1).Female_2$.

The vector of parameters of interest is

$$\theta = \Big(\theta_1^{low}, \theta_1^{ds,high}, \theta_1^{sd,high}, (\alpha_1^{high} - \alpha_2^{high}), (\alpha_1^{low} - \alpha_2^{low}) \Big).$$

The utility from providing a $q_{i,h}$ level of education for each child [$u_{i,h} = a_{i,h}.(q_{i,h})^{\delta_{i,h}^{low}} - \alpha_i^{low} q_{i,h}$ or $u_{i,h} = a_{i,h}.(q_i)^{\delta_{i,h}^{high}} - \alpha_i^{high} q_{i,h}$] in the parents utility has two parts: the benefit and the

[9]The utility function for households with more than 2 children is presented in Appendix B.

cost parts. Note that $a_{i,h}$ and $q_{i,h}$ are complementary in the benefit part of the utility from providing a $q_{i,h}$ level of education to child i in household h. In other words, holding everything else fix, parents get higher utility by providing higher $q_{i,h}$ to child i compared to child j if $a_{i,h} > a_{j,h}$.

Assumption 1: $a_{i,h}$ of a child i in household h is drawn from a distribution $G(.)$, with the constraint that $\sum_{i=1}^{N_{c_h}} a_{i,h} = 1$. I assume that $G(.)$ is not dependent of gender or birth order.

The incorporation of differences in δ across the children's genders and the household's gender composition within the model allows for the consideration of disadvantage that females face at the extensive and intensive margin in terms of human capital investment when they have a brother. This feature accounts for the varying investment in education based on the child's gender, reflecting potential gender disadvantage that may exist within the household— as evidenced in Figure 8. The assumed functional form is designed to capture the idea that girls with brothers receive a penalty in the distribution decision of the education resources made by parents. Additionally that penalty is an increasing function of the proportion of boys among the siblings.

Similarly, the model's incorporation of differences in α across children's birth order enables the examination of the monotonic increase in education attainment as birth order advances. This acknowledges the tendency for education levels to rise sequentially with the child's position within the family birth order— as observed in Figure 9.

The integration of these elements into the model, allows for a more comprehensive understanding of the factors influencing educational outcomes, and facilitates the identification of potential areas for intervention to address gender-related disparities and birth order effects on educational attainment. To estimate the vector of parameter θ, I used an indirect inference approach. In particular a simulated method of moments (SMM) approach. The procedure is outlined in the next section. The parameters are estimated for each level of education of parents.

5.3 Estimation and Inference Strategy

In this section, I provide an overview of the data moments utilized to identify the key parameters in the model. These data moments serve as essential empirical inputs that align the model's predictions with the observed real-world outcomes.

For the estimation of the parameters, I use two set of moments. The first set of moments includes two moments. Firstly, I consider the difference in average education of daughters and average education of sons from households with a mix of genders and no uneducated children, while holding fix parents' education and number of children. This difference in educational outcomes can be attributed solely to gender disadvantage within households, making it a critical determinant in identifying the parameters involved in δ^{low}. By isolating the impact of gender disadvantage on educational disparities, this moment provides a valuable means of disentangling the specific effects of gender-related preferences within the model. Secondly, I consider the average education attainment by birth order in households with children of the same gender only (either only daughters or only sons) and no uneducated children, holding fix the years of education of the head of household, and the number of children in the household. These average educational levels for different birth orders are used to calculate the differences in average education attainment between successive birth orders. These differences play a fundamental role in uniquely identifying the parameter associated with the opportunity costs ($\alpha_{(i)}^{low}$).

The second set of moments used involves the proportion of educated daughters and the proportion of educated firstborn children by gender composition of households with an uneducated child, holding fix parents' education and number of children. This allows me to uniquely identify parameters in δ^{high}, and $\alpha_{(i)}^{high}$. In particular the proportion of educated firstborn children in households with only children of the same gender and one uneducated child, is used to estimate $\alpha_{(i)}^{high}$. Similarly the proportion of educated firstborn daughters and second born daughters are used to estimate $\theta_1^{ds,high}$, and $\theta_1^{sd,high}$ respectively.

For the rest of the analysis, let's define the variables Y_h^d as daughters' education in household h and Y_h^s as sons' education in the same household h. And let's Y_h^1, Y_h^2, be the education of firstborn and second born children respectively. Additionally, let Z represent a vector comprising the observables, specifically the education of the head of the household, the number of children (N_c), and the gender composition of children. Note that for households with the same observed (Z) and unobserved (ν) types, any differences observed in the variables Y_h^d and Y_h^s, or in Y_h^1 and Y_h^2 between these households stem from disparities in the unobservable difference in children's ability. This unobservable component captures the variability in educational outcomes such as parental ability-based preferences that influence educational investment decisions within households, that cannot be explained by the observable characteristics.

Given the defined notations and functional form, the inference procedure proceeds as follows. First, I simulate H households, each with $N_c = 2$ number of children, possible gender composition (from { only sons, only daughters, firstborn son and second born daughter, firstborn daughter and second born son }) and q_T, which mirror the distribution of those variables observed in the actual data sample of households. In a second step, for a fixed $\delta^{high}_{i,h}$, $\delta^{low}_{i,h}$, and $(\alpha_t)_{t=1}^{N_c-1}$, I solve the maximization problem in equation 11 for s draws of $\left\{(a_{i,h})_{i=1}^{N_{c_h}}, \text{ with } \sum_{i=1}^{N_{c_h}} a_{i,h} = 1\right\}$ for each of the H simulated households. This procedure yields the following model predictions:

1. $S^d_d = s \times H^d$ predictions of the education of daughters in households with only daughters, where H^d is the number of simulated households with only daughters.

2. $S^b_d = s \times H^b$ predictions of the education of daughters in households with both genders, where H^b is the number of simulated households with both genders.

3. $S^i_d = s \times H^d$ predictions of the education of the i^{th} born daughter in households with only daughters.

4. $S^i_s = s \times H^s$ predictions of the education of the i^{th} born son in households with only sons, where H^s is the number of simulated households with only sons.

These predicted education attainments represent the educational outcomes based on the given parameter values. I then take the average of the S^m_l predictions for each moment, where $l, m \in \{s, d, b\} = \{\text{only sons, only daughters, both gender}\}$.

To do inference on the parameters in δ^{low}, the model and data moments are matched across various gender compositions. This process involves normalizing the parameter γ and estimating θ_1 by matching the model's predictions with the observed data in terms of the difference in educational attainment for daughters and sons from households with both genders.

To do inference on the parameters $(\alpha^{low}_{(t)})_{t=1}^{N_c}$ associated with birth order, the model and data moments are matched across different birth orders. This process entails normalizing $\alpha_{(N_c)}$ and estimating $(\alpha_{(t)})_{t=1}^{N_c-1}$ by comparing the model's predictions to the observed data regarding the difference in educational attainment between t^{th} and $(t+1)^{th}$ born children.

To do inference on the parameters δ^{high}, and $(\alpha^{high}_{(t)})_{t=1}^{N_c}$, the data moments and the model moments on the proportion of educated firstborn children from one gender households, firstborn daughter, and second born daughters from mix gender households are matched with the model moments.

Let $\hat{\mu}^d_l(\theta, Z)$ represent the predicted average education attainment of daughters in different household types, where $l \in d, s, b$ denotes households with only daughters, only sons, and both genders, respectively. Similarly, let the vector $\hat{\mu}(\theta, Z) = (\hat{\mu}_1(\theta, Z), \ldots, \hat{\mu}_{N_c}(\theta, Z))$, be the predicted average education attainment by birth order. Finally, let $\hat{\pi} = (\hat{\pi}_1, \hat{\pi}_{fb,d}, \hat{\pi}_{sb,d})$, be the model prediction of the proportions of firstborn children, of firstborn daughters and second born daughters for households with an uneducated child. These simulations provide estimates of the model's predictions for various household compositions, gender and birth orders, allowing for the comparison of the model's outcomes with the observed data. The data moments are defined as follows:

5.3.1 Moments Matched

Let T_{educ} be the total number of educated children.
Data Moments Matched:

- $m_1 = E[Y^d|Gender\_Comp = d, T_{educ} = 2] - E[Y^d|Gender\_Comp = b, T_{educ} = 2]$,
- $m_2 = E[1\{Y^1 > 0\}|Gender\_Comp = s, T_{educ} = 1]$,
- $m_3 = E[1\{Y^d > 0\}|Gender\_Comp = b^{d,s}, T_{educ} = 1]$,
- $m_4 = E[1\{Y^d > 0\}|Gender\_Comp = b^{s,d}, T_{educ} = 1]$,
- $m_{t+4} = E[Y|birth\_order = t + 1] - E[Y|birth\_order = t],\ t \in \{1, \ldots, N_c\}$.

I matched the following data and model moments to estimate θ.

$$m_1 = \hat{\mu}^d_d - \hat{\mu}^d_b,\ m_2 = \hat{\pi}_1,\ m_3 = \hat{\pi}_{fb,d},\ m_4 = \hat{\pi}_{sb,d} \text{ and } m_{t+4} = \hat{\mu}_{t+1} - \hat{\mu}_t;\ t \in \{1, \ldots N_c - 1\}.$$

The corresponding sample objective function is the following expression:

$$\hat{Q}(\theta, Z = z) = (\bar{Y}^d_{d,z} - \bar{Y}^d_{b,z} - (\hat{\mu}^d_{d,z} - \hat{\mu}^d_{b,z}))^2 + (\hat{m}_2 - \hat{\pi}_1)^2 + (\hat{m}_3 - \hat{\pi}_{fb,d})^2 + (\hat{m}_4 - \hat{\pi}_{sb,d})^2 + \quad (13)$$

$$\sum_{l \in \{d,s\}} \sum_{t=1}^{N_c - 1} (\bar{Y}^l_{t+1,z} - \bar{Y}^l_{t,z} - (\hat{\mu}^l_{t+1,z} - \hat{\mu}^l_{t,z}))^2$$

$$\hat{\theta} = \ \text{argmin}_{\theta \in \Theta} \hat{Q}(\theta).$$

The sample objective function possess a unique optimizer (See Figure).

5.3.2 Estimation of G(.)

I utilized auxiliary data to estimate the parameters of $G(.)$ outside of the model. In particular, I assume that the ability-based parents' preference for children are i.i.d from a Beta distribution.

$$a_i \sim^{i.i.d} Beta(\beta_1, \beta_2) \text{ with } \sum_{i=1}^{N_c} a_i = 1$$

β_1 and β_2 are estimated using auxiliary data. Specifically, I used data on average GPA in junior high school for a sample of student in Benin in 2018 to estimate β_1 and β_2 using maximum likelihood method. The Beta distribution seems to be a good fit for the distribution of relative ability (See Figure 24).

5.4 Standard Errors

The variance-covariance matrix for parameter estimates is given by the following expression:

$$\Omega = \Big[\frac{\partial m(\theta)'}{\partial \theta}\Big|_{\hat{\theta}} V^{-1} \frac{\partial m(\theta)}{\partial \theta}\Big|_{\hat{\theta}}\Big]^{-1}$$

where, the partial derivative of the model function $\frac{\partial m(\theta)}{\partial \theta}$ is obtained numerically as,

$$\frac{\partial m(\theta)}{\partial \theta}\Big|_{\hat{\theta}} = \frac{m(\hat{\theta}+h) - m(\hat{\theta})}{h}$$

and, the variance-covariance matrix of the data moments, denoted as V, is computed through bootstrapping the data N times. This involves repeatedly calculating the moments N times and then using these N observations of the moments to determine the covariance between them. The standard errors are derived as the square roots of the diagonal elements of the matrix Ω.

5.5 The Model's Performance

In this section, the performance assessment of the model is conducted through a series of exercises. Leveraging the estimated parameters $\hat{\theta}$, the household maximization problem is solved, yielding the optimal distribution $q_h^\star$ of q_{T_h} among children within each household h across a simulated sample of H households. Subsequently, $q^\star$ is utilized for several analytical purposes. Initially, it is employed to quantify the intra-household educational differentials between daughters and sons, as well as between firstborn and second-born children. These computations are juxtaposed against corresponding differentials derived from empirical education attainment data. A visual comparison between the distributions generated by the model and those observed in the data is presented in Figure 17, demonstrating a noteworthy concordance. Furthermore, $q^\star$ is harnessed to derive targeted moments for estimation, alongside selected non-targeted moments. These analytical outcomes are succinctly summarized in Figure 18. There is no significant difference between the model and the data for most of the targeted moments and some of the non-targeted moments as well.

6 Model predictions and Counterfactual Analysis

6.1 Results and Model Predictions

The estimates of θ are provided in Table 8 for households with $N_c = 2$ and non-educated and college educated parents. The estimation results reveal that both at the extensive and intensive margins households with non-educated head of households exhibit higher values for the gender disadvantage parameter when compared to households with college educated parents. This is in line with the reduced form results, which suggest that college-educated parents are less biased against daughters in terms of education based on the comparison of educational outcomes between daughters and sons in households with college-educated parents versus non-educated parents. In particular, $\hat{\theta}_1^{ds,high} = 0.119$, $\hat{\theta}_1^{sd,high} = 0.13$ and $\hat{\alpha}_1^{high} = 0.02$ for non-educated parents.

This suggests that, on average, for parents without formal education and high constraints to have an uneducated child, the likelihood of the firstborn child being educated compared to a second-born child of the same gender is approximately 0.3663, which correspond to an average cost difference of 0.02. To illustrate, if it costs 2500 USD [10] to provide a high school education for a second-born child, it would require an additional 445 USD to provide the same level of education for the firstborn child in families without formal education. That corresponds to an average annual difference of $\approx$ \$37. This difference represents around 10% of Benin's GDP per capita in the 1990s, where the education decisions for the children in our sample are made.

Moreover, they perceive that investing in the education of the second-born son yields on average a 31% higher utility compared to investing the same resources in the education of the firstborn daughter. Similarly, their utility is estimated to be 34% higher for the firstborn son compared to the second-born daughter. Note that estimates for the extensive margin parameters ($\hat{\theta}_1^{ds,high}$, $\hat{\theta}_1^{sd,high}$ and $\hat{\alpha}_1^{high}$) are not provided for college-educated parents, as nearly all of them, approximately 98%, have educated children.

At the intensive margin, $\hat{\theta}_1 = 0.0239$, and $\hat{\alpha}_1 = 0.0013$ for non-educated parents. For college educated parents, $\hat{\theta}_1 = 0.0115$, and $\hat{\alpha}_1 = 0.0016$. This indicates that parents without formal education perceive a 6.2% higher utility on graduating high school for sons compared to daughters, while for college-educated parents, the difference is approximately 3%. The cost difference between providing up to high school education for firstborn compared to second born conditional on both being educated represents only 1.3% of Benin's GDP per capita in the 1990s for non-educated parents.

[10] This is the estimated cost of completing high school in Benin in 2003 (Foko et al. (2012))

This disparity in the estimates of parameters between non-educated and college educated parents can be explained by a couple of key factors. First, college-educated parents often highly value education— they have an extreme aversion to having an uneducated child— and are more likely to prioritize educational opportunities for all their children, regardless of gender. They might view education as a means of empowerment and advancement, and thus, they are more likely to invest equally in the education of both daughters and sons. In addition, college-educated parents often have higher incomes and socioeconomic status, which can provide more resources for their children's education. This increased financial stability can mitigate concerns about the perceived need to prioritize sons' education over daughters'. Second, college-educated parents might be more aware of gender biases and stereotypes in society, including those related to education. They may actively work to counter these biases by ensuring equal opportunities for their children. Finally, there could be generational and cultural shifts at play, where younger, college-educated parents are more likely to challenge traditional gender roles and expectations regarding education. Overall, while these are potential reasons, it's important to note that biases can still exist in any household, regardless of educational background. However, the data presented in the passage suggests a trend where college-educated parents appear to be less biased against daughters in terms of educational opportunities within their households.

6.2 Counterfactual Analysis

In this section, I provide contextual interpretations of the parameters within the model, shedding light on their real-world implications and the underlying mechanisms influencing distribution of education resources within households. I did this through two key counterfactual analyses, which allow me to explore the potential effects of policy interventions and alternative scenarios. These counterfactual analyses allow for a broader exploration of the model's predictions under different conditions, helping to identify potential strategies to address educational inequalities and promote equitable educational opportunities for all children. The contextual interpretations and counterfactual analyses together contribute to a comprehensive evaluation of the model's insights and provide valuable guidance for policymakers and researchers in devising effective measures to improve educational outcomes and reduce disparities within diverse household contexts.

6.2.1 Counterfactual 1: Interaction between Gender, birth order, and unobserved ability

In this first counterfactual analysis, my main objective is to interpret the parameters θ by quantifying the additional level of ability required to counterbalance educational inequality resulting from gender and birth order effects, respectively. To achieve this, I compute the extra ability needed by daughters and elder siblings to offset the effect of gender and birth order disadvantages on their education attainment. In order to do that I solve the household maximization problem in equation 11 with (using $\hat{\theta}$) and without (setting $\theta = 0$) disadvantages for a grid of relative ability of children for two-child families with a firstborn daughter and a second-born son, and compute the following quantity:

1. Ability of the firstborn daughter relative to the second born son at which the average difference between daughter's and son's education is equal to zero in presence of disadvantages.
2. The change in inequality due to gender and birth order disadvantages, by level of relative ability of the firstborn daughter.

Figure 16 presents the first counterfactual analysis for non-educated and college educated parents at the intensive margin. It suggests three main conclusions. First, for the same ability draws, gender and birth order disadvantages reduce the education attainment of the first born daughter by $\approx$ 4.6 and 2.2 for non-educated parents and college educated parents respectively. Second, the average difference between firstborn daughters and second born sons is equal to 0 in the presence of gender and birth order effects when the firstborn daughter's ability draw is $\approx$ 13% (resp. 8%) higher than the ability draw of the second born son for households with non-educated head of household, (resp. households with college educated head of household).

6.2.2 Counterfactual 2: Education Policies

In situations where there is no inherent disadvantage against daughters or firstborn children, the primary factor leading to differences in education within a household between daughters and sons lies in variations in their individual abilities. Assuming that the initial abilities of children are distributed independently of their gender and birth order, the average difference in education between daughters and sons, in the absence of any gender and birth order effects, forms a symmetric distribution centered around 0. However, this distribution shifts towards the negative side in instances when gender and birth order disadvantages are present.

Simply put, in the absence of gender and birth order effects, the distribution of the average education difference between daughters and sons exhibits first-order stochastic dominance over its counterpart in scenarios where gender and birth order effects exist (See Figure 19). The education policies considered in this section are implemented among non-educated parents only.

Compulsory Education Policy

The objective of this section is to examine the efficacy of a policy focusing on the extensive margin, wherein all parents are forced to have educated children. Figure 21 displays the distribution of the difference in education between daughters and sons in panel (a), and between firstborn and second-born children of the same gender in panel (b), across three distinct scenarios. The black curve represents the empirical distribution when gender and birth order disadvantages against daughters and firstborn children exist. The red curve, on the other hand, depicts the distribution in the absence of such gender and birth order biases. Lastly, the pink curve illustrates the distribution when gender and birth order disadvantages at the extensive margin are eradicated.

The elimination of the extensive margin gender and birth order disadvantages proves effective at both reducing gender and birth order effects and overall average inequality. In particular, the distribution of the difference between daughters' and sons' (resp. firstborn and second born children's) educations under the compulsory education policy second order stochastically dominates both the distributions with and without gender (and birth order) effects. This means that, compared to the scenarios with and without these disadvantages, the compulsory education policy leads to more favorable and equitable educational outcomes. The overall distribution shifts in a way that is consistently better, resulting in a notable reduction in average inequality across the sample.

In summary this compulsory education type of policy reduces part of the gender and birth order effects on the within household educational inequality. In addition, overall average inequality is reduced by 55% in mixed gender households and 50% in one gender households. However, the gender effect got reduced by 63% whereas birth order effect got reduced by 78%. That is consistent with the fact that gender effect is equally present in both the extensive and intensive margin where as the birth order effect is mostly present in the extensive margin.

Comparative Statics of Increase in Education Resources: Education Voucher Policy

This section delves into the analysis of how a non-targeted increase in total education resources among non-educated parents affects the impact of gender and birth order disadvantages on within-household inequality. Initial empirical findings reveal that the average education level of children from college-educated parents with two educated adult children is 14.5, while it stands at 9.2 for children from non-educated parents. In addition almost all college educated parents have only educated children.

The exercise conducted in this section involves an exogenous increase in the average education level of children from non-educated parents, raising it from approximately 9.2 to 14.5 combined with the compulsory education type of policy like the one describe in the previous section. Subsequently, the household's maximization problem is solved with this new average and $\hat{\theta}$. Finally, a comparison is drawn between the education differences of daughters and sons in this new scenario against the original disparities observed for non-educated and college-educated parents.

The results are depicted in Figure 22. The Figure suggests that this non-targeted increase in education resources combined with a compulsory education policy leads to decrease in inequality against daughters with non-educated parents compared to the original disparities. When compared with daughters of college educated parents, the gender bias is still higher— as twice as high compared to college educated parents—. In addition gender effect is reduced by 56%— which is smaller than the reduction observed with the compulsory education alone in the previous section—. However, overall average inequality reduced by $\approx$ 50%. The distribution of the difference between daughters' and sons' educations with non-educated parents under this policy is very close to the distribution for college educated parents, especially in households where the sons have higher draw of ability. In summary, the analysis suggests that the non-targeted increase in education resources, aiming to improve overall educational outcomes, does not reduce the gender effect among non-educated parents to the same level as college educated parents but did reduce overall average inequality.

Targeted Cost Reduction Policy

The objective of this section is to identify an education cost reduction strategy that would result in an education distribution between daughters (resp. firstborn children) and sons (resp. second born children) resembling scenarios where no gender and birth order disadvantages exist, even in the presence of such biases. The cost reduction policy encompasses the following measures:

1. At the extensive (resp. intensive) margin remove cost difference between firstborn and second born. This corresponds to $\approx$ 1.9% (resp. $\approx$ 0.2%) reduction in schooling cost for firstborn children.

2. At the extensive (resp. intensive) margin reduced schooling cost for firstborn daughters.

This corresponds to $\approx 3\%$ (resp. $\approx 1.3\%$) reduction in schooling cost for daughters compared to sons.

3. At the extensive (resp. intensive) margin reduced schooling cost for second daughters. $\approx 3.8\%$ (resp. This corresponds to $\approx 1.3\%$) reduction in schooling cost for daughters compared to sons.

Figure 20 displays the distribution of the average education difference between daughters and sons in panel (a), and between firstborn and second-born children of the same gender in panel (b), across three distinct scenarios. The black curve represents the empirical distribution when disadvantages against daughters exist. The blue curve depicts the distribution in the absence of such biases. In the red curve, we observe the distribution when disadvantages persist, but a cost reduction policy is implemented. By construction, the cost reduction policy effectively mirrors the distribution in scenarios devoid of disadvantages. Note that this cost reduction policy did not change significantly the overall average inequality among non-educated parents.

The following Table summarize the effectiveness of these different education policies counterfactual.

Table 1: Summary of Education Policies Counterfactual

	Reduce gender & birth order effects	Eliminate gender & birth order effects	Reduce overall inequality
Education voucher	✓	×	×
Compulsory education	✓	×	✓
Targeted educ cost reduction	✓	✓	×

7 Robustness of Estimates to Missing Siblings

The main sample used for this analysis comprises adult children who were living in the same household as their parents during the census period. This sample represents a specific subgroup within the larger population of adult children. Importantly, the decision for children to leave the parental home is often influenced by factors such as their occupation and educational accomplishments, making it an endogenous process. Moreover, the motives for leaving home frequently differ between daughters, commonly associated with marriage, and sons. Given these dynamics, there's a potential for bias in our estimates. This would be particularly concerning if, firstly, the children who remained at home are more similar to each other, and secondly, if they significantly differ from those who moved out. The wide range in both educational attainment and gender among children residing in the same household as their parents suggests that the first concern may not be significant.

7.1 Gender Effect

The second concern could lead to either overestimation— if women who moved out are more educated compared to ones who stayed and men who moved out are less educated compared to the ones who stayed— or underestimation— if women who moved out are less educated and men who moved out are more educated, compared to those who remained at home.

In this section, I delve into the potential bias in estimating the effect of gender disadvantage on within-household inequality. To investigate this, I compare the educational attainment of adult women and men living in the same households as their parents to those who have moved out. The mean comparison between these two groups is presented in Figure 25. This comparison suggests that the difference in average education between men and women is more pronounced in the sub-sample that is not included in my analysis. In addition we observe a clear first order stochastic dominance between the empirical distribution of the education of adult female living in the same households as their parents and those who do not (see Figure 26). Such first order stochastic dominance is not as pronounced among men. As a result, it implies that, if anything, I may be underestimating the effect of gender disadvantage. Consequently, my estimate of gender disadvantage can be interpreted as an estimate of the lower bound of the true parameter.

7.2 Birth Order Effect

A similar argument to the one presented in the previous section also applies to the birth order disadvantage parameter. The decision for children to move out is closely linked to their age, with older children being more inclined to leave their parents' household. Consequently, we may have a selected sample of younger children in some households. In specific cases, children referred to as firstborns in certain households might actually be of a higher birth order. Additionally, more accomplished younger siblings may have already moved out. It's important to note that both of these situations would potentially bias our estimate of the birth order disadvantage parameter downward. In particular, if we maintain the assumption that firstborn children receive less education than other children, the older firstborn children with less education— who already moved out of the family house— are not included in our analysis. This leads to an underestimation of the birth order effect. In addition if high educated children are more likely to move out— because they have better and stable socio-economic status— we observe uniformly less educated children in our sample. In summary, we are likely to have in our sample, less educated children. On one hand, if the age effect dominates the education effect, we will have less firstborn children in our sample, which biases our estimate downward. On the other hand, if the education effect dominates the age effect, we have less second born children in our sample, which also biases our estimate downward.

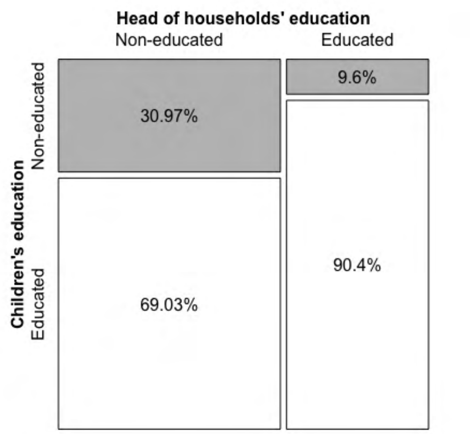
8 Conclusion

In this paper, I examine the interaction between the three empirically known sources of disparities in children's educational attainment within households. I constructed a structural model of households' distribution of education resources among children, allowing for the influence of factors such gender, birth order and ability of children. The model not only allows me to decompose, for each relative ability draw, the total observed inequality into parts due gender, birth order, and ability differences; it also gives a platform for analysing how different education policies affect within household inequalities.

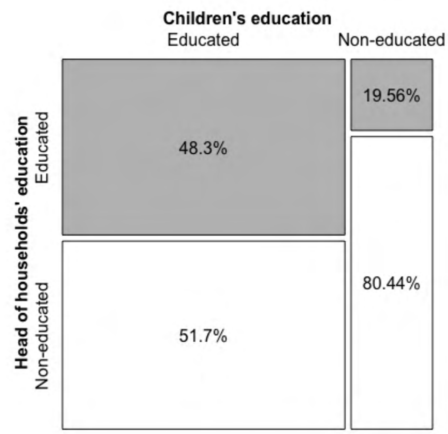
The construction of the model is motivated by contexts similar to the one of Benin; a setting marked by notable disparities in children's education within households, coupled with evidence of gender and birth order disadvantages. To ensure tractability, certain aspects of the parental decision-making process regarding education resources distribution are omitted. Notably, the model adopts a static approach, although the education decision of children is inherently dynamic. The primary objective of the paper being to rationalize the observed differences in children's education, attributing them to gender disadvantages, birth order disadvantages, or variations in innate ability draws; despite its static nature, the model proves relevant, as it effectively incorporates and analyzes the interactions among these three factors. Additionally, the paper attributes any unexplained differences in children's education, not accounted for by gender and birth order, to differential draws of innate ability. However, it acknowledges the potential influence of other unobserved factors, such as varying preferences of mothers in polygamous households, which could lead to increased parental investment in the education of specific children. In recognizing this, the interpretation of unexplained inequality within households is acknowledged as an upper bound of the effect of differential ability.

In light of the findings in this paper, we can expect a reduction in the opportunity cost of girls education such as education support in the form of cash transfers, scholarships, and school kits for girls; to reduce within household inequality in children's education that is due to gender disadvantage. Additionally, a reduction in the opportunity cost of education for firstborn, such as cash transfers and school kits, to young parents (first-time parents) or scholarships for firstborn children; is expected to reduce within household inequality in children's education that is due to birth order disadvantage. However, these two policies need to be combined for an effective reduction in disadvantaged-based inequality. This is due to the possibility of displacement of disadvantage from one group to another. In particular, if the policy only targets firstborn children, the disadvantage against daughters might increase, and vice versa. Finally, a compulsory education policy is the most effective in reducing average inequality in the sample. However, as long as there is budget constraint, as we move toward maximum education for everybody, there will always be a positive within household inequality.

9 Tables and Figures

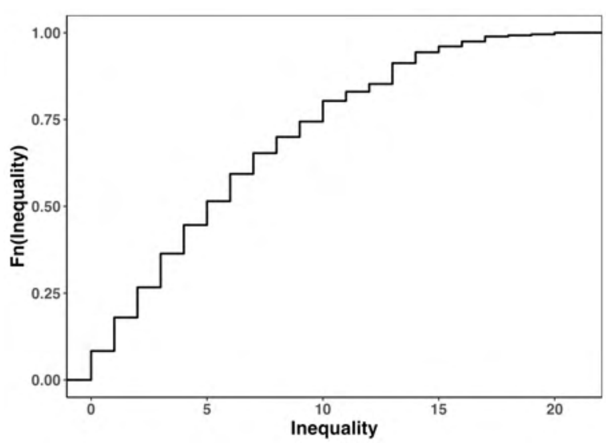


(a) Children's education as function of parents' education

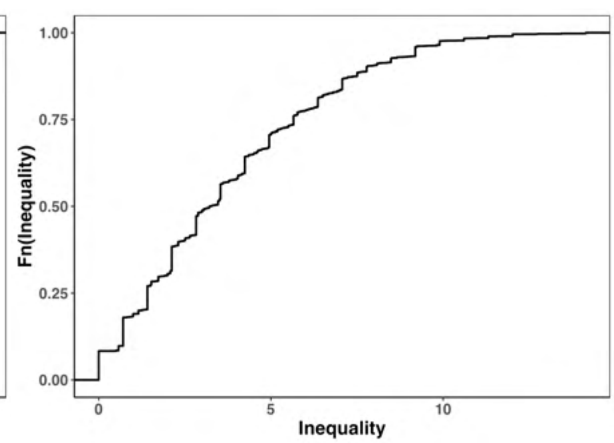


(b) Parents' education as function of children's education

Figure 2: Parents and children's education.

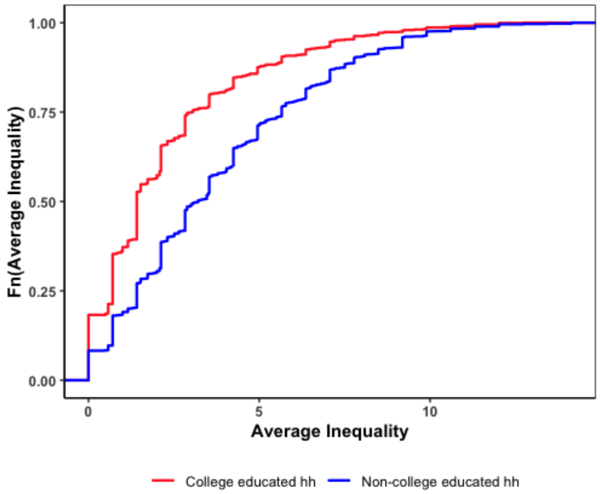


(a) Range

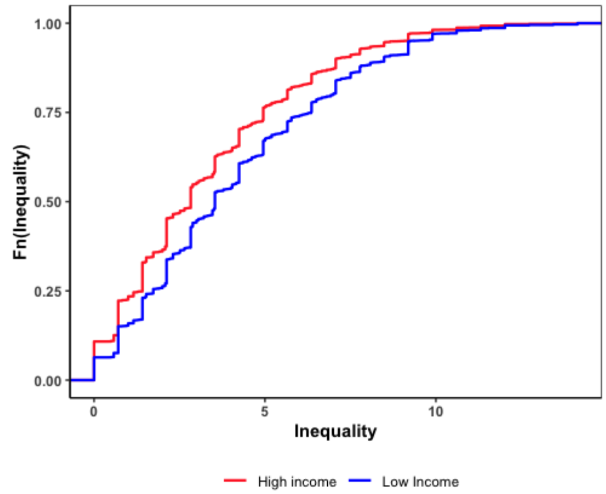


(b) Standard Deviation

Figure 3: Empirical cdf of within household range and standard deviation of education attainment of children.



(a) Parents Education



(b) Household Wealth Index (HWI)

Figure 4: Distribution of inequality by socio-economic groups.

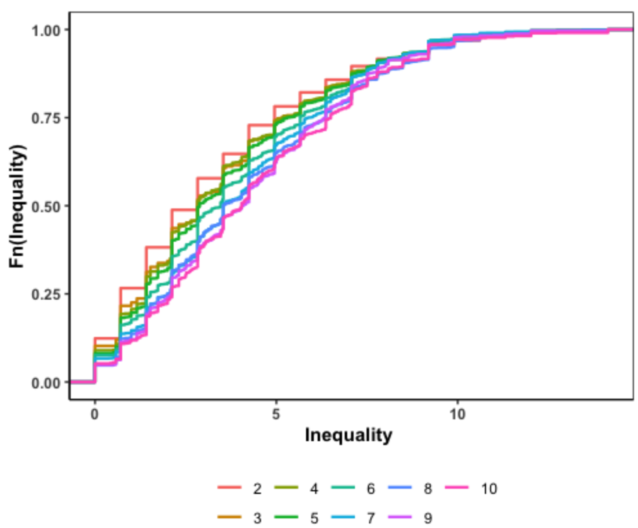


Figure 5: Distribution of inequality by number of children.

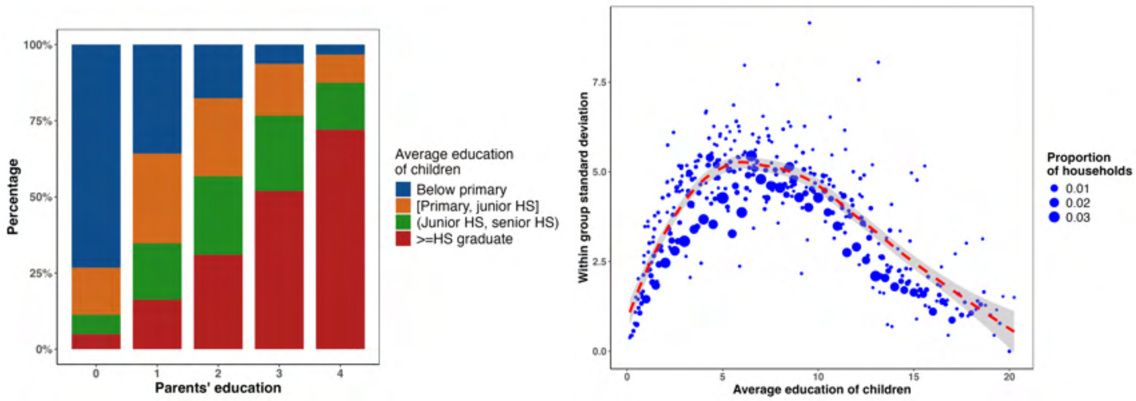


Figure 6: Distribution of average education attainment of children.

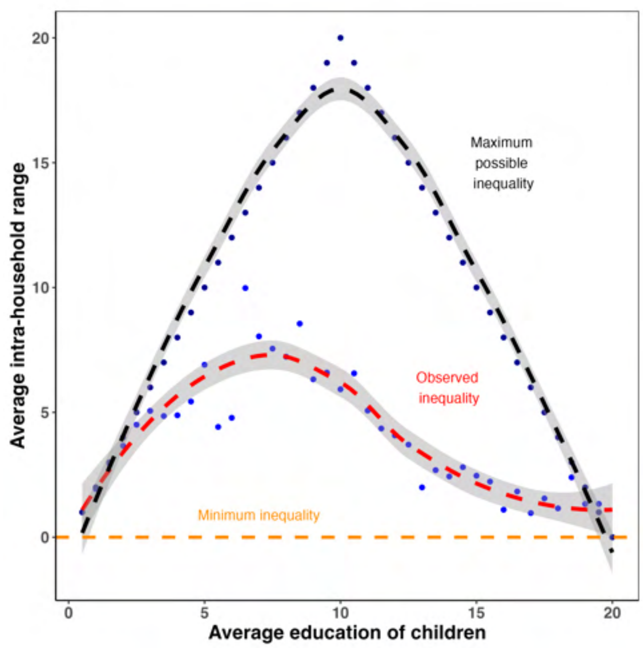


Figure 7: Within household standard deviation of children's education as function of average education of children (Min vs. Max vs. Observed for $N_c = 2$).

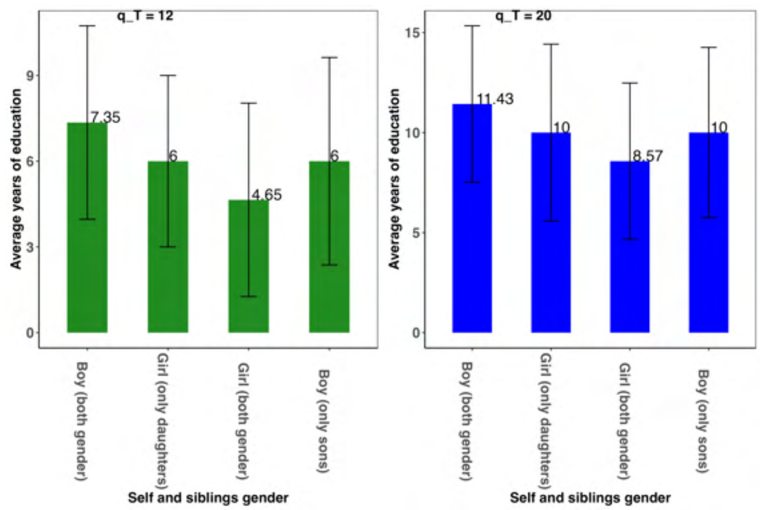


Figure 8: Average years of education by gender and households gender composition ($N_c = 2$)

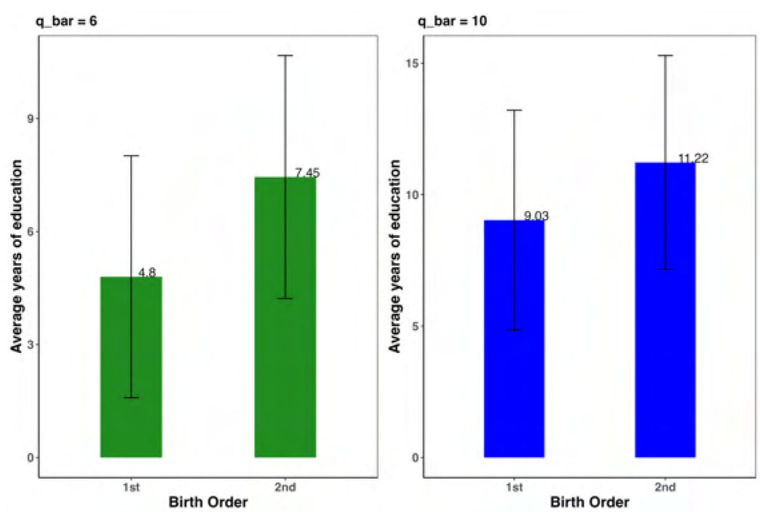
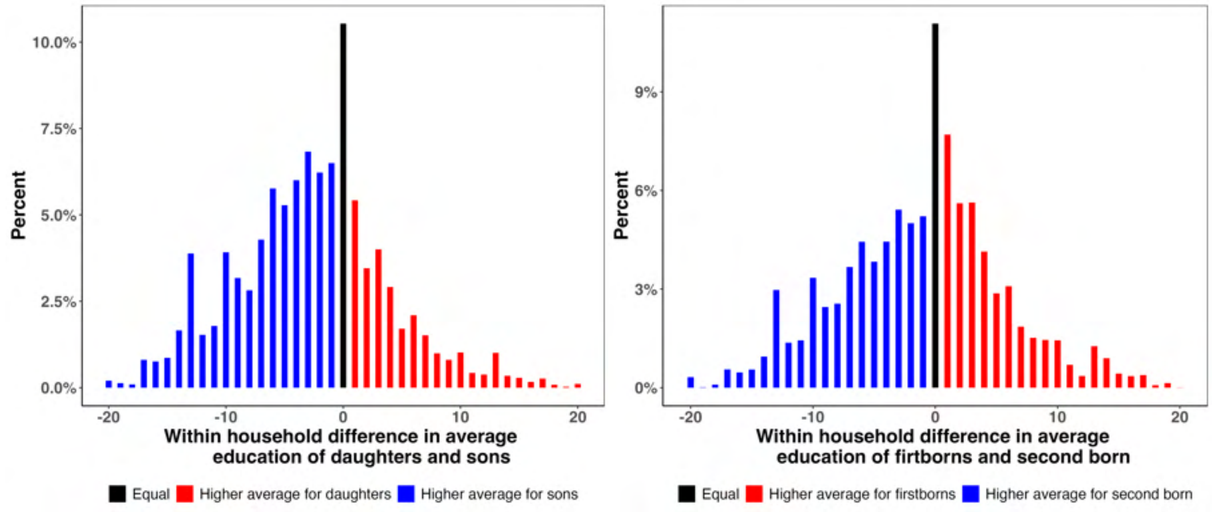
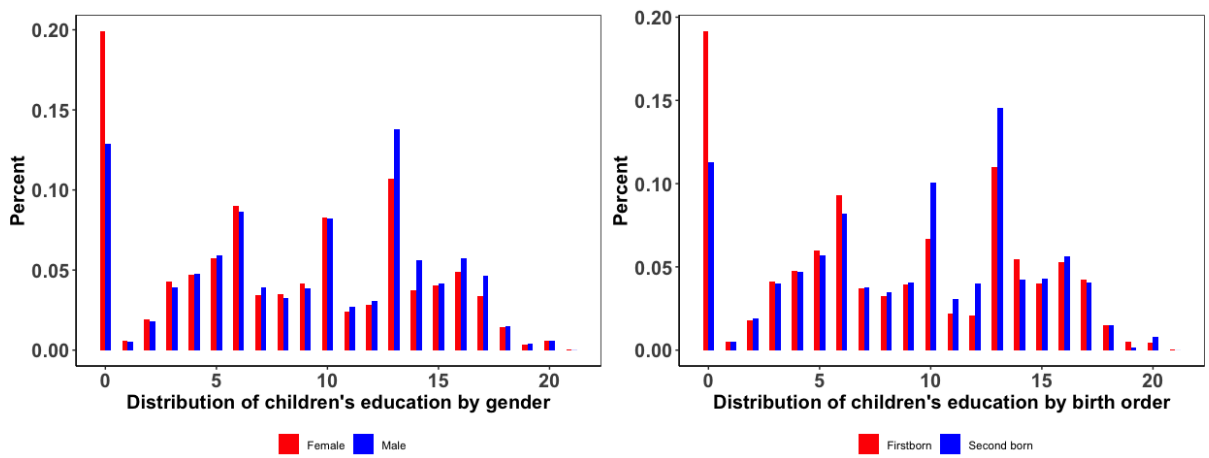


Figure 9: Average years of education by birth order ($N_c = 2$)



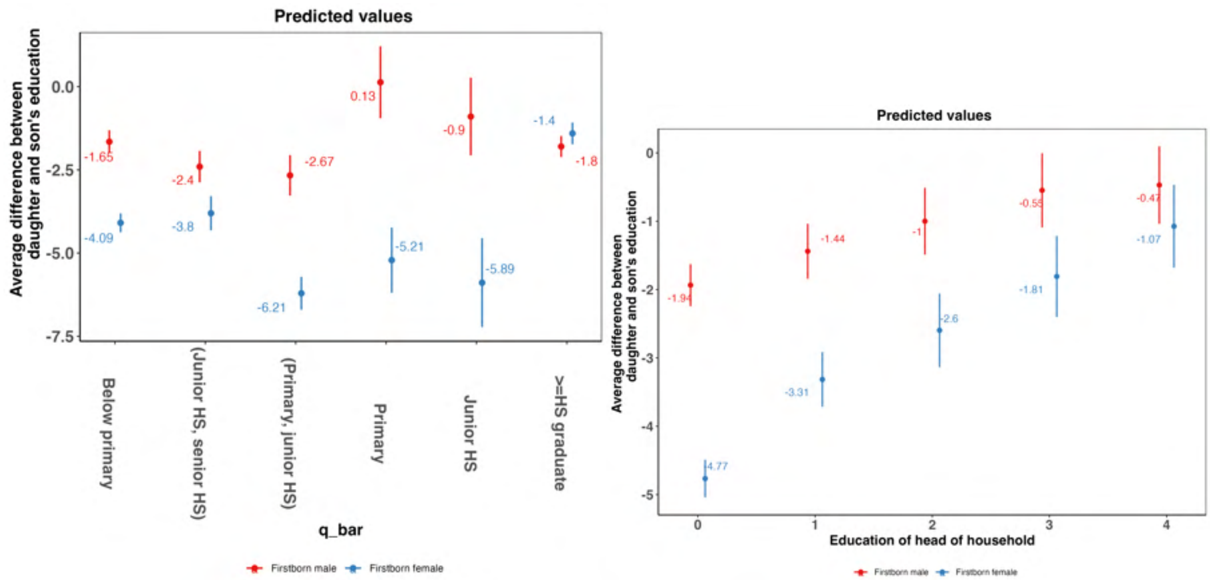
(a) Between daughters and sons ($N_c = 2$) (b) Between 1st and 2nd born ($N_c = 2$)

Figure 10: Histogram of within household difference in average education (Benin, 2013)



(a) By gender (b) By birth order

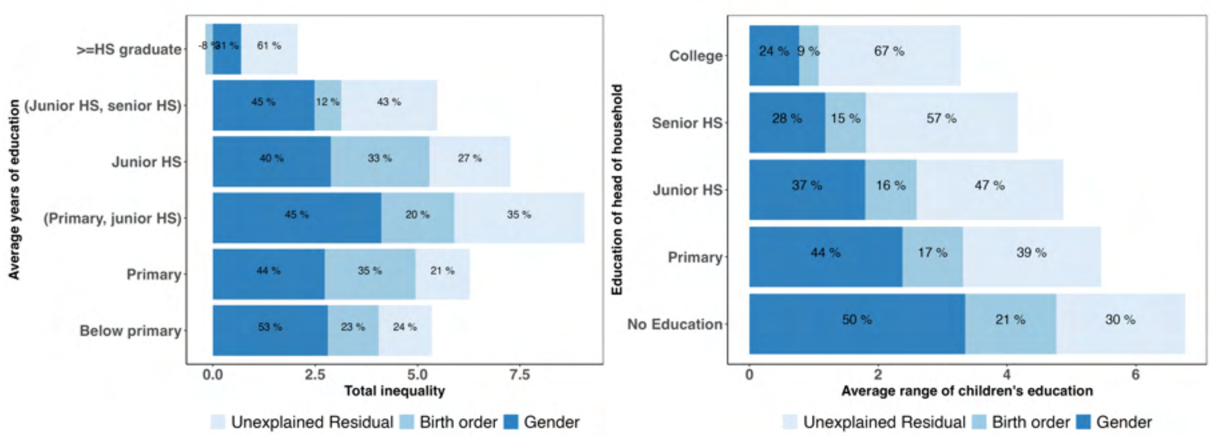
Figure 11: Distribution of children's education for number of $N_c = 2$ (Benin, 2013)



(a) As function of within household average education of children

(b) As function of head of household's education

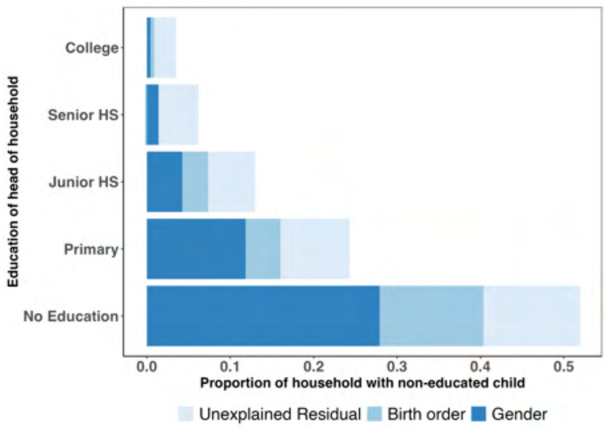
Figure 12: Effect of gender and birth order disadvantages on within household inequality ($N_c = 2$)



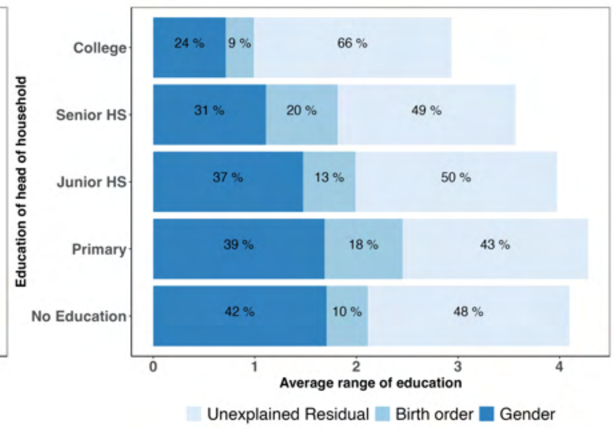
(a) As function of within household average education of children

(b) As function of head of household's education

Figure 13: Inequality decomposition ($N_c = 2$)

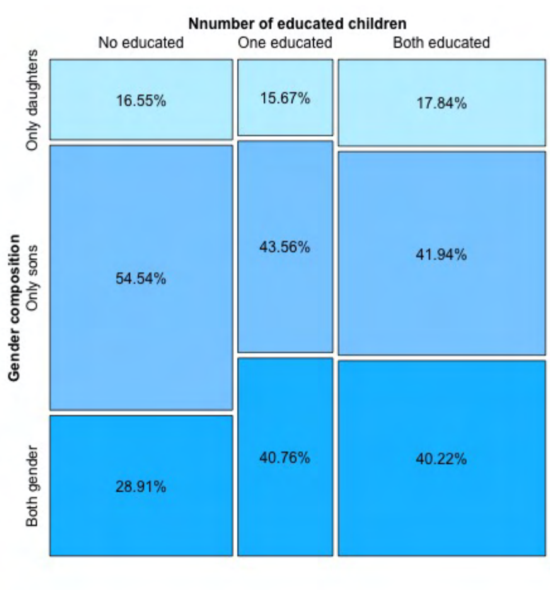


(a) Extensive Margin

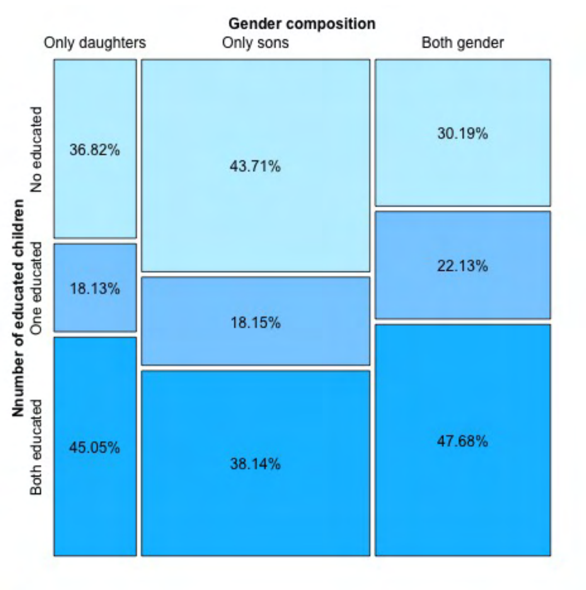


(b) Intensive margin

Figure 14: Inequality decomposition as function of head of household's education ($N_c = 2$)

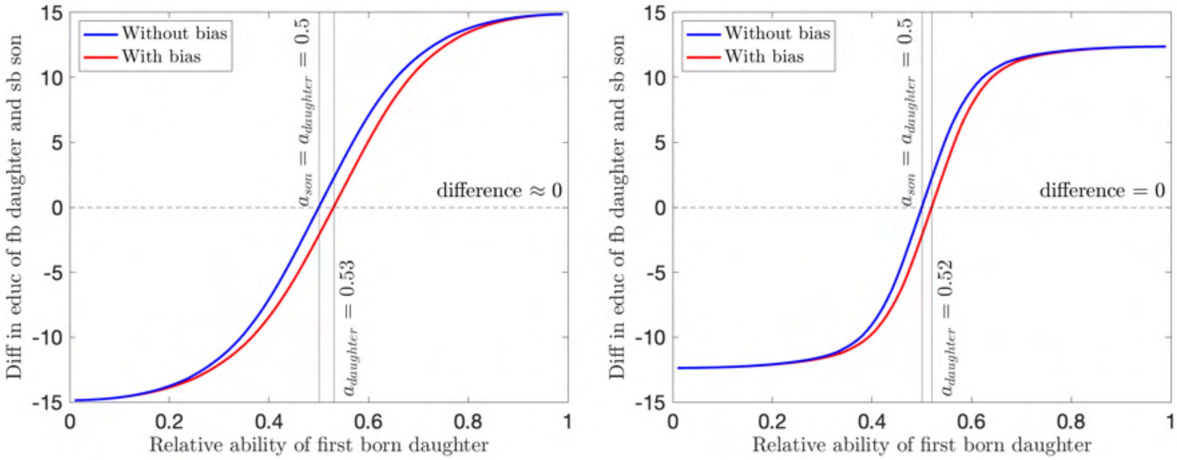


(a) Gender composition of households as function of number of uneducated children



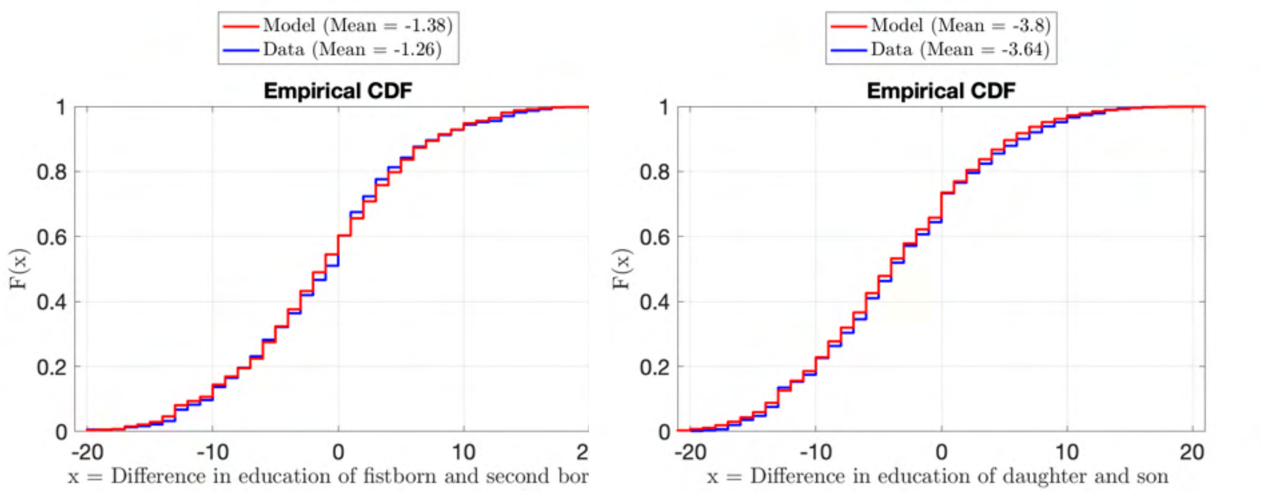
(b) Number of uneducated children as function of gender composition of households

Figure 15: Number of uneducated children by gender composition ($N_c = 2$)



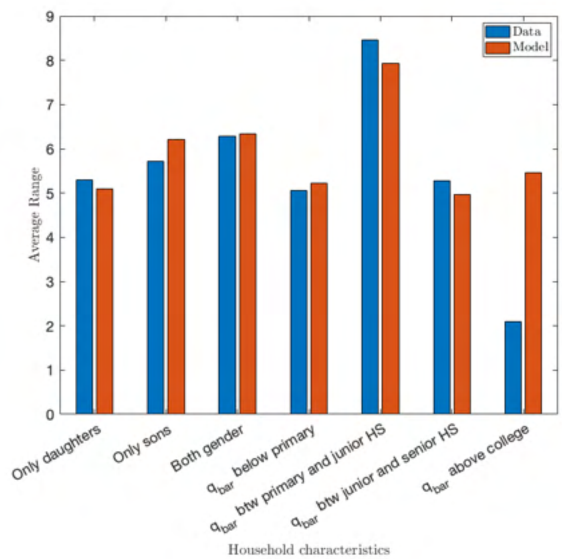
(a) Non-educated head of household (b) College educated head of households

Figure 16: Effect of gender and birth order disadvantages on inequality ($N_c = 2$)

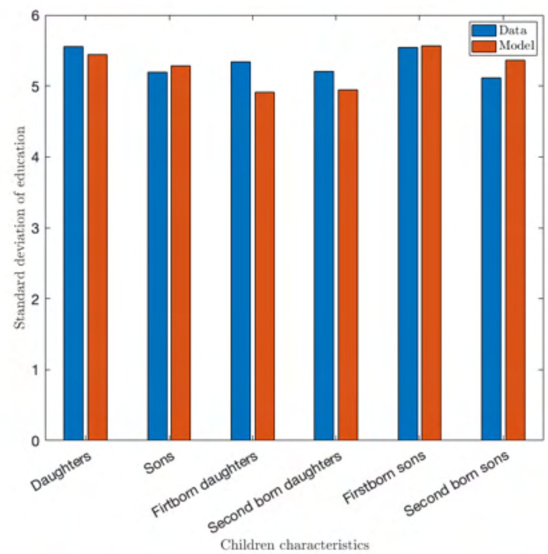


(a) Firstborn vs. second born (b) Daughter vs. son

Figure 17: Empirical distribution of key moments: Data vs. Model ((For non-educated parents))

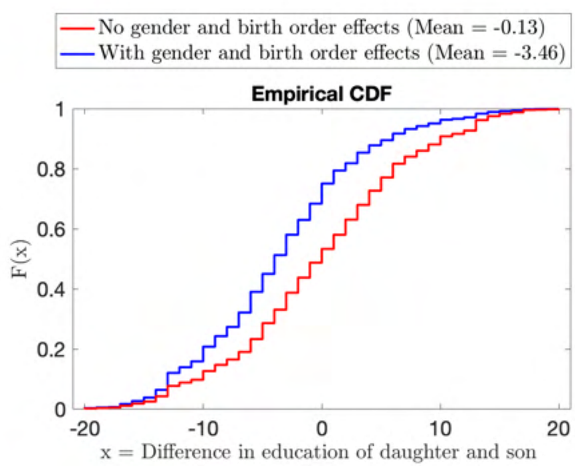


(a) Average range

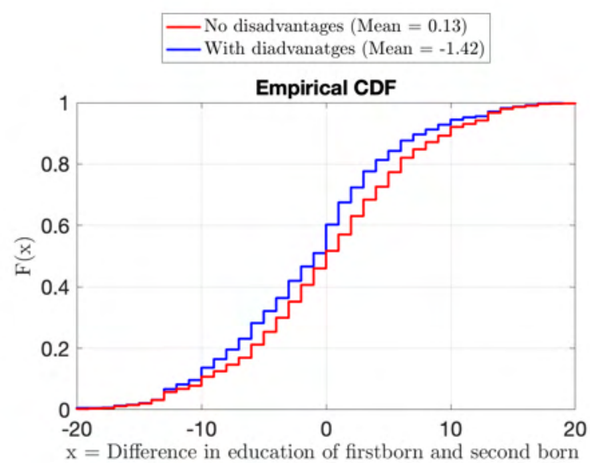


(b) Standard deviation

Figure 18: Data vs Model moments (For non-educated parents)

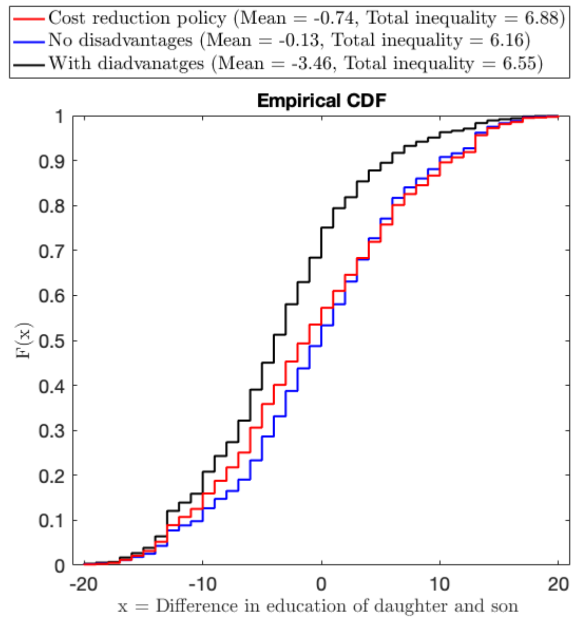


(a) Daughter v.s son

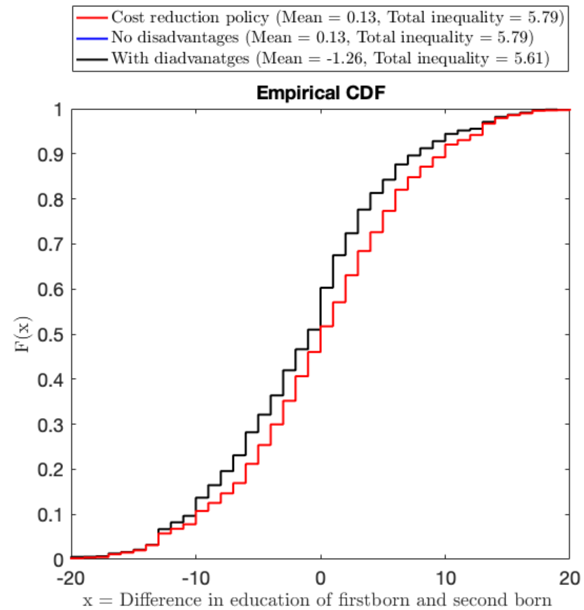


(b) Firstborn v.s second born

Figure 19: Distribution of the difference in children's education ($N_c = 2$)

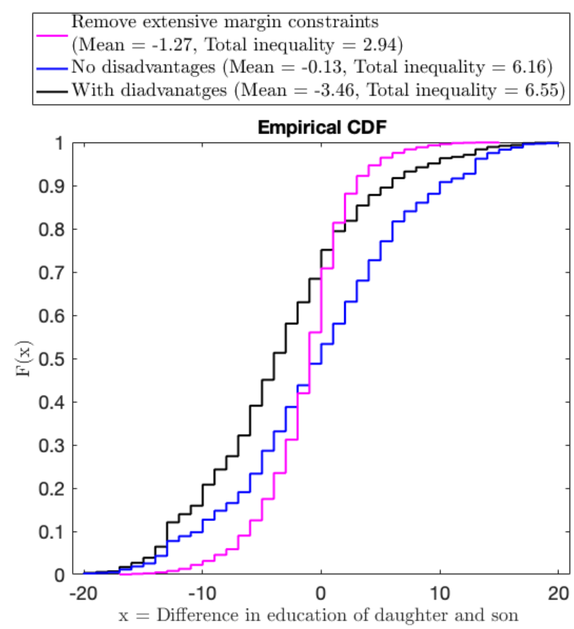


(a) Daughter v.s son

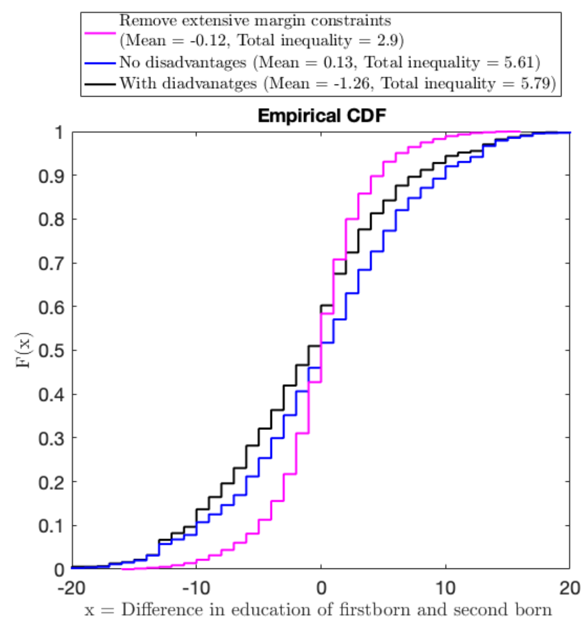


(b) Firstborn v.s second born

Figure 20: Distribution of the difference in children's education for non-educated parents ($N_c = 2$) [Observed vs. with targeted cost reduction policy]

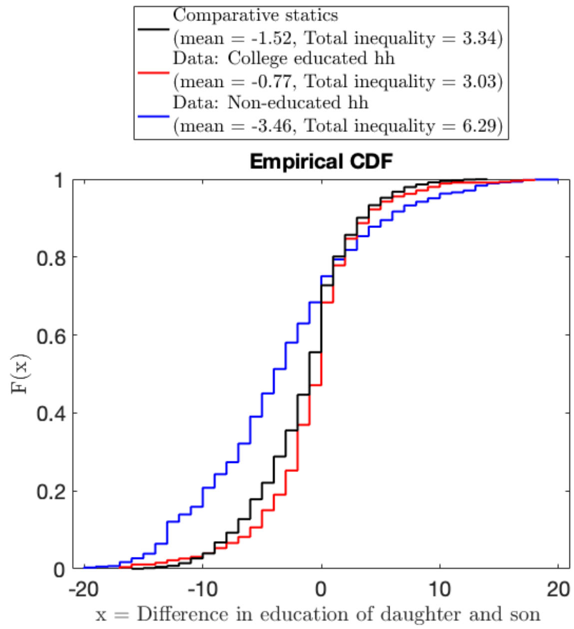


(a) Daughter v.s son

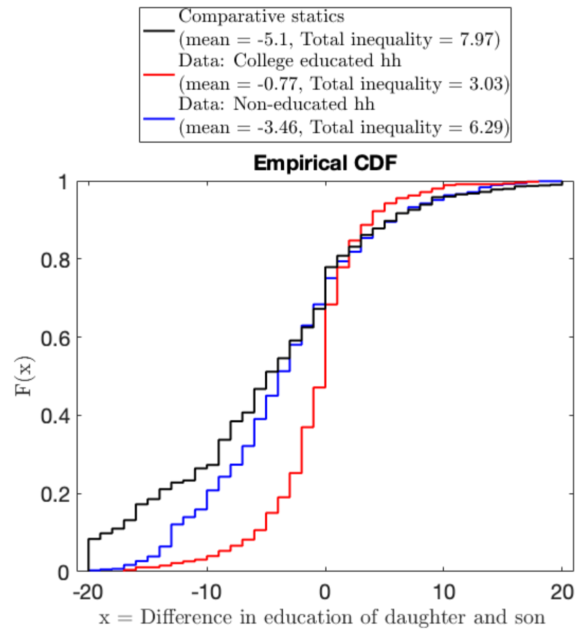


(b) Firstborn v.s second born

Figure 21: Distribution of the difference in children's education for non-educated parents ($N_c = 2$) [Observed vs. with compulsory education policy]



(a) Education voucher with compulsory education



(b) Education voucher without compulsory education

Figure 22: Distribution of difference in daughter and son's education [for non-educated parents [observed and after an education voucher policy] and college educated parents]

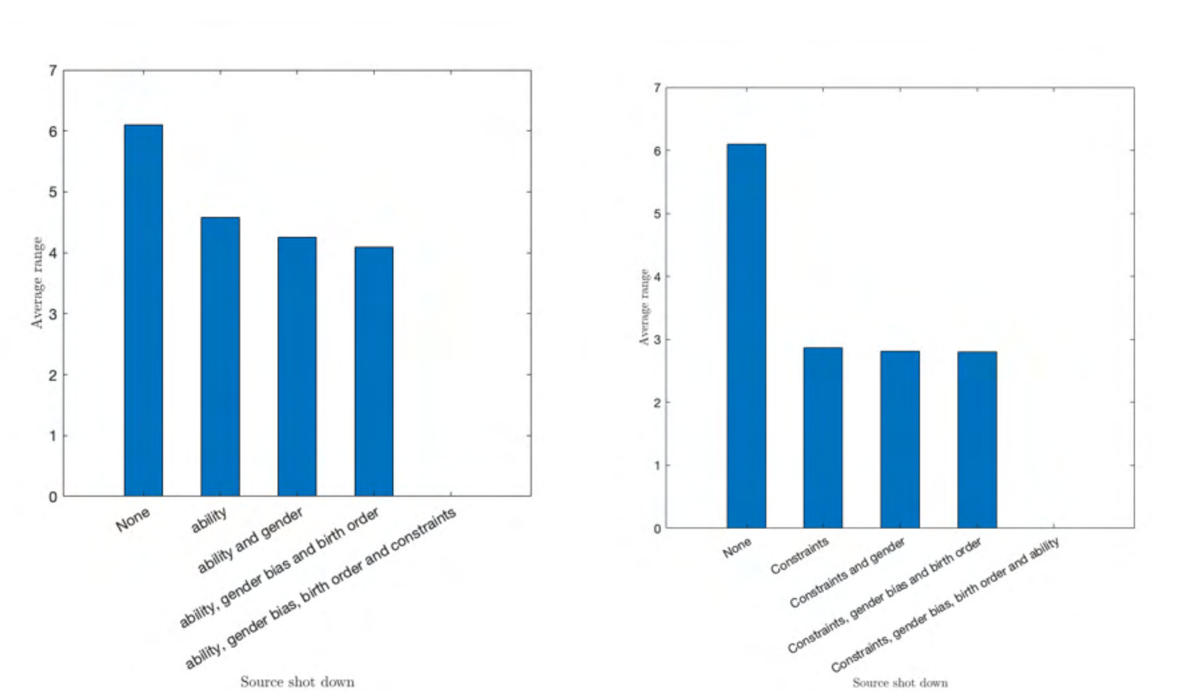


Figure 23: Average Inequality after subsequent shot down of sources of inequality

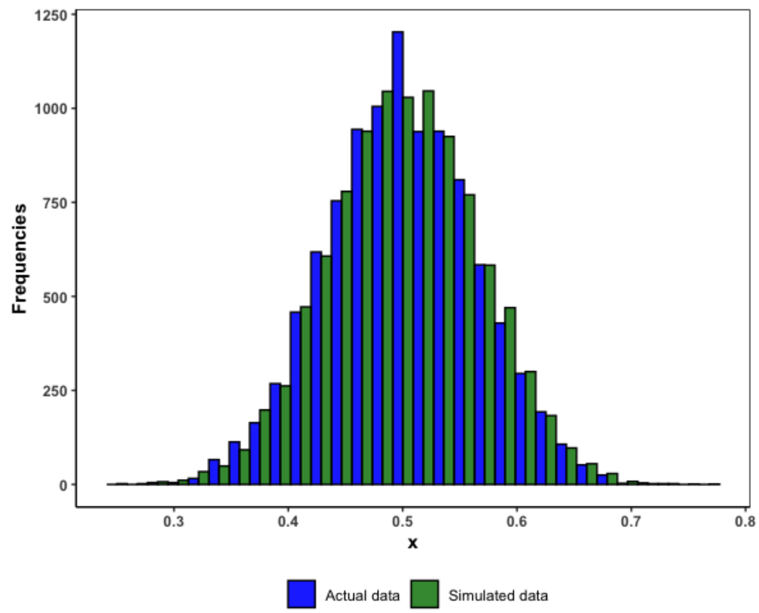
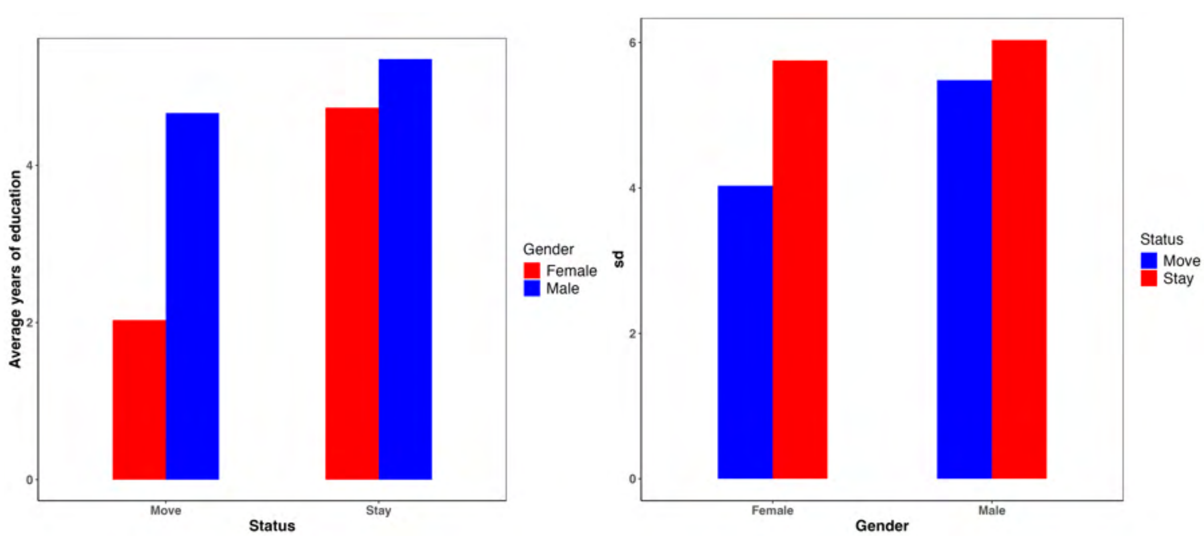


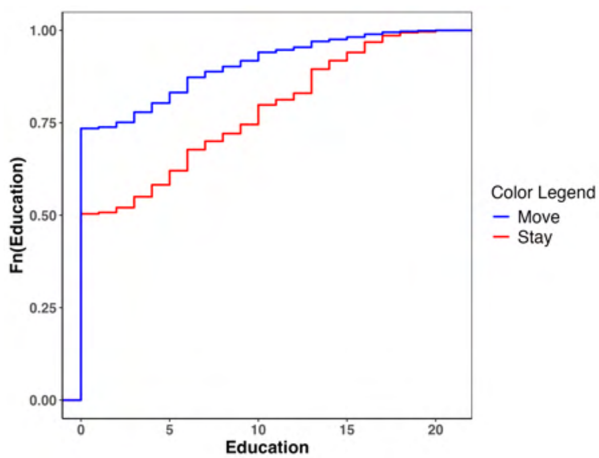
Figure 24: Histogram of relative GPA in junior high school and histogram of random draws from Beta (28.82, 28.78).



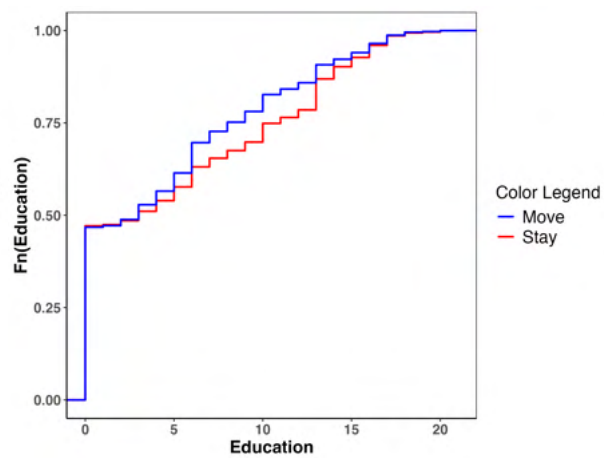
(a) Mean

(b) Standard Deviation

Figure 25: Mean and standard deviation of adult between 25 and 40 years old



(a) Women



(b) Men

Figure 26: Empirical cdf of the years of education of adults between 25 and 40 years old

Tables

Table 2: Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Age	89,594	29.452	3.993	25	40
Female	89,594	0.380	0.485	0	1
Years of education	89,594	7.760	5.802	0	21
At least one years of education	89,594	0.776	0.417	0	1
Range of children's education	89,594	6.821	4.873	0	21
Standard deviation of children's education	89,594	3.874	2.744	0.000	14.142
Educated head of household	85,407	0.390	0.488	0	1
Number of children between 25 and 40	89,594	3.055	1.557	2	16
Number of children	89,594	6.340	4.354	2	79
Educated with educated head of household	85,407	0.353	0.478	0	1
Non-educated with non-educated head of household	89,594	0.180	0.384	0	1
$\bar{q}$	89,594	7.760	4.444	0.143	20.250
q_T	89,594	22.354	15.660	1	148

Table 3: Regression of within household maximum years of education on within household inequality and of within household standard deviation of children's education on households' characteristics

	Maximum years of education				Standard deviation		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(Intercept)	9.40*	6.16*	11.94*	10.24*	4.24*	1.46*	0.87*
Standard deviation	0.50*	0.66*					
$\frac{1}{N_c}\sum_{i=1}^{N_c} 1\{q_i = q_{\max}\}$			−1.35*	−2.64*			
hh Educ = Primary		1.05*		0.71*	−0.77*	−0.62*	0.02
hh Educ = Junior HS		2.62*		2.14*	−1.17*	−0.66*	0.86*
hh Educ = Senior HS		4.24*		3.56*	−1.59*	−0.47*	2.98*
hh Educ = College		5.74*		4.93*	−1.94*	0.24*	4.75*
Average years of education ($\bar{q}$)						0.91*	1.16*
$\bar{q}^2$						−0.06*	−0.07*
hh Educ = Primary:$\bar{q}$							−0.29*
hh Educ = Junior HS:$\bar{q}$							−0.56*
hh Educ = Senior HS:$\bar{q}$							−0.94*
hh Educ = College:$\bar{q}$							−1.14*
hh Educ = Primary:$\bar{q}^2$							0.02*
hh Educ = Junior HS:$\bar{q}^2$							0.04*
hh Educ = Senior HS:$\bar{q}^2$							0.05*
hh Educ = College:$\bar{q}^2$							0.06*
Number of children		0.04*		0.05*		0.04*	0.05*
HWI		0.45*		0.38*		−0.10*	−0.10*
Urban		0.89*		0.71*		−0.32*	−0.32*
Christian		0.90*		0.74*		−0.28*	−0.27*
Both gender		0.31*		0.42*		0.20*	0.22*
R^2	0.10	0.31	0.00	0.16	0.04	0.22	0.24
Num. obs.	32729	32729	32729	32729	32729	32729	32729

* Null hypothesis value outside the confidence interval.

Table 4: Regression of children's education on their gender and birth order with household fixed effect ($N_c = 2$)

	(1)	(2)	(3)	(4)	(5)	(6)
	$q_T = 12$		$q_T = 20$		All q_T	
Female	-3.03^*		-2.75^*		-2.46^*	
First born	-3.24^*	-1.90^*	-2.59^*	-2.61^*	-0.95^*	-1.24^*
Firstborn female	1.26^*		0.38		-0.27^*	
R^2	0.21	0.09	0.11	0.09	0.67	0.70
Adj. R^2	−0.59	−0.82	−0.79	−0.83	0.34	0.40
Num. obs.	1632	300	1558	278	43970	7562
RMSE	4.39	3.91	5.71	5.76	4.52	4.23
Household fixed effects	✓	✓	✓	✓	✓	✓
Average inequality (Both gender: Firstborn female)	6.23		7.22		5.84	
Average inequality (Only daughters)	3.81		6.01		4.59	
Average inequality (Only sons)	5.07		6.09		5.08	
	Explained proportion					
Gender	50.1%	-	38.1%	-	33.7%	-
Birth order	30.5%	49.9%	35.9%	43.4%	29.3%	32.9%
Unexplained	19.6%	50.1%	26%	56.6%	37%	67.1%

* Null hypothesis value outside the confidence interval.

Note: Columns (2), (4), and (6) are for households with only daughters. For households with only sons the decomposition is 19% birth order + 81% ability.

Table 5: Regression of children's education on their gender and birth order with household fixed effect ($N_c = 2$)

	(1)	(2)	(3)	(4)	(5)	(6)
	Non-educated parents		College educated parents		All	
Female	−3.16*		−0.90*		−2.47*	
Firstborn	−1.19*	−1.55*	−0.41	−0.13	−0.93*	−1.24*
Firstborn female	−0.39*		0.25		−0.34*	
R^2	0.58	0.60	0.68	0.69	0.67	0.70
Num. obs.	22540	3528	1884	478	40884	6956
Household fixed effects	✓	✓	✓	✓	✓	✓
Average inequality (Both gender: Firstborn female)	6.76		3.27		5.84	
Average inequality (Only daughters)	5.29		3.16		4.59	
Average inequality (Only sons)	5.71		2.78		5.08	
	Explained proportion					
Gender	47.2%	-	36%	-	33.7%	-
Birth order	23%	29.3%	4%	4.1%	29.3%	32.9%
Unexplained	29.8%	70.7%	60%	95.9%	37%	67.1%

* Null hypothesis value outside the confidence interval.

Note: Columns (2), (4), and (6) are for households with only daughters. For households with only sons the decomposition is respectively 17% birth order + 83% ability for college educated parents and 21% birth order + 79% ability for non-educated parents. For the whole sample it is 18% birth order + 82% ability.

Table 6: Regression of children's education on their gender and birth order with household fixed effect (Extensive vs Intensive margin) ($N_c = 2$)

	Non-educated parents		College educated parents		All	
	Extensive	Intensive	Extensive	Intensive	Extensive	Intensive
	(1)	(2)	(3)	(4)	(5)	(6)
Female	−0.54*	−1.73*	0.05	−0.94*	−0.52*	−1.38*
Firstborn	−0.23*	−0.39*	0.11	−0.47*	−0.22*	−0.29*
Firstborn Female	−0.05	0.05	−0.35	0.45	−0.05	−0.25*
R^2	0.21	0.71	0.03	0.71	0.20	0.75
Num. obs.	10166	12374	62	1822	12846	28038
Household fixed effects	✓	✓	✓	✓	✓	✓

* Null hypothesis value outside the confidence interval.

Table 7: Educational inequality on average education

	(1)	(2)	(3)	(4)	(5)	(6)
	Full sample		Non-educated hh		College educated hh	
Average education ($\bar{q}$)	1.25*	1.04*	1.44*	1.26*	0.87*	0.64*
	[1.24; 1.27]	[1.02; 1.07]	[1.42; 1.46]	[1.23; 1.29]	[0.81; 0.94]	[0.54; 0.75]
$\bar{q}^2$	−0.08*	−0.06*	−0.09*	−0.08*	−0.05*	−0.04*
	[−0.08; −0.08]	[−0.06; −0.06]	[−0.09; −0.09]	[−0.08; −0.08]	[−0.05; −0.04]	[−0.04; −0.03]
R^2	0.69	0.71	0.73	0.74	0.61	0.62
Covariates		✓		✓		✓
Num. obs.	32729	32729	19558	19558	1438	1438

* Null hypothesis value outside the confidence interval. Covariates include parents' education, area of residence, religion, number of children, and gender composition of the household.

Table 8: Estimates of $\hat{\theta}$, ($N_c = 2$)

	Non-educated parents					College educated parents	
	$\hat{\theta}_1^{low}$	$\hat{\theta}_1^{ds,high}$	$\hat{\theta}_1^{sd,high}$	$\hat{\alpha}_1^{low}$	$\hat{\alpha}_1^{high}$	$\hat{\theta}_1^{low}$	$\hat{\alpha}_1^{low}$
Estimates	0.0239**	0.119**	0.13**	0.0013**	0.02**	0.00759**	0.00045**
Standard errors	0.0014	0.0004	0.0036	0.0028	0.0013	0.0006	0.0012
Number of observations			11,270			942	

$**$ significant at 5% level of significance.

10 Appendix A

10.1 Appendix A1: Proof of Claim 1

$$\Delta_{daughter-son} Educ_h = \beta_0 + \beta_1 Firstborn\_daughter_h + \varepsilon_h$$

$$E\Big[|\Delta_{daughter-son} Educ|\Big] = E\Big[|\beta_0 + \beta_1 Firstborn\_daughter + \varepsilon|\Big]$$

By Jensen's inequality,

$$E\Big[|\beta_0 + \beta_1 Firstborn\_daughter + \varepsilon|\Big] \geq \Big|E\Big[\beta_0 + \beta_1 Firstborn\_daughter + \varepsilon\Big]\Big|$$

$$E\Big[\Big|\beta_0 + \beta_1 Firstborn\_daughter + \varepsilon\Big|\Big] \geq \Big|\beta_0 + \beta_1 E[Firstborn\_daughter] + \underbrace{E[\varepsilon]}_{\text{Assumed to be 0}}\Big|$$

Therefore, $E[Range] \geq |\beta_0 + \beta_1 E[Firstborn\_daughter]|$

Hence, $E[Range|$ household has firstborn daughter$] \geq |\beta_0 + \beta_1|$

10.2 Appendix A2: Model for households with Number of Children equal 3

For $N_c = 3$, Let

$$U(q_h, \theta) = \sum_{type} \Big\{ \nu_h^{type}. \sum_{i=1}^{3} e_i^{type}. \Big[a_i.(q_i)^{\delta_{i,h}^{type}} - \alpha_i^{type} q_i\Big]\Big\} \text{ where,} \tag{14}$$

- $\nu^{type} \sim Multinomial(p)$, with $p = (p_0, p_1, \ldots, p_2)$, and $\sum_{t=0}^{2} p_t = 1$
- $\delta_{i,h}^{type} = \gamma - \theta_1^{type} Female_i \frac{1}{N_c - 1} \sum_{\{i,j \in h\}, j \neq i} (1 - Female_j)$,
- with $type \in \{low(L), medium(M), high(H)\}$

For households with 3 children, aversion for having uneducated children takes three possible values (High: H/ Medium: M/ Low: L). Households with high aversion for having an uneducated child choose to educate both children. Households with medium aversion choose to educate 2 of their children, whereas households with low aversion choose to educate only child out of the three children. For those who choose to educate two children and only one child, choose the educated children based on a draw ν_h^M and ν_h^H.

$$e_i^M = 1\{\exists j : \big(a_i.(q_i)^{\delta_{i,h}^M} - \alpha_i^M q_i\big) > \big(a_j.(q_i)^{\delta_{j,h}^M} - \alpha_j^M q_j\big)\},$$

$$e_i^H = 1\{\big(a_i.(q_i)^{\delta^H_{i,h}} - \alpha_i^H q_i\big) > \big(a_j.(q_i)^{\delta^H_{j,h}} - \alpha_j^H q_j\big), \forall j \neq i\},$$

They are derived from the following constraints:

$$\sum_{i=1}^{3} e_i^M = 2 \text{ and } \sum_{i=1}^{3} e_i^H = 1$$

The vector of parameters of interest is

$$\theta = \Big(\theta_1^L, \alpha^L_{(1)} - \alpha^L_{(2)}, \alpha^L_{(2)} - \alpha^L_{(3)}, \theta_1^M, \alpha^M_{(1)} - \alpha^M_{(2)}, \alpha^M_{(2)} - \alpha^M_{(3)}, \theta_1^H, \alpha^H_{(1)} - \alpha^H_{(2)}, \alpha^H_{(2)} - \alpha^H_{(3)}\Big)$$

The dimension of θ is 1×9.

Table 9: Estimates of $\hat{\theta}$, $(N_c = 3)$

	$\hat{\theta}_1^L$	$\hat{\alpha}_1^L - \hat{\alpha}_2^L$	$\hat{\alpha}_2^L - \hat{\alpha}_3^L$	$\hat{\theta}_1^M$	$\hat{\alpha}_1^M - \hat{\alpha}_2^M$	$\hat{\alpha}_2^M - \hat{\alpha}_3^M$	$\hat{\theta}_1^H$	$\hat{\alpha}_1^H - \hat{\alpha}_2^H$	$\hat{\alpha}_2^H - \hat{\alpha}_3^H$
Estimates	0.033**	0.0026**	0.0010*	0.0761**	0.0094*	0.0001**	0.1596**	0.0120**	0.0105**
Standard errors	0.0052	0.0006	0.0006	0.0058	0.0016	0.0019	0.0073	0.0019	0.0015
Number of observations					3644				

$**$ significant at 5% level of significance, $*$ significant at 10% level of significance.

10.3 Appendix A3: Generalized Households' utility function for any Number of Children

Let $type \in \{0, 1, \ldots N_c - 1\}$, where

- 0 corresponds to the least constrained to have a non-educated child,
- and $N_c - 1$ corresponds to constrained to have $N_c - 1$ non-educated children.

$$U(q_h, \theta) = \sum_{c=2}^{3} \Big\{ 1\{N_{c_h} = c\}. \sum_{type} \Big\{ \nu_h^{c,type}. \sum_{i=1}^{c} e_i^{c,type}. \Big[a_i.(q_i)^{\delta^{type}_{i,h}} - \alpha_i^{type} q_i\Big]\Big\}\Big\} \text{ where,} \quad (15)$$

- $\nu_h^{c,\cdot} \sim Multinomial(p_{c,\cdot})$, with $p_{c,\cdot} = (p_{c,0}, p_{c,1}, \ldots, p_{c,N_c-1})$, and $\sum_{type=0}^{N_c-1} p_{c,type} = 1$
- $\delta^{type}_{i,h} = \gamma - \theta_1^{type} Female_i \frac{1}{N_{c_h}-1} \sum_{\{i,j\in h\}, j\neq i}(1 - Female_j)$,
- $\sum_{i=1}^{c} e_i^{c,type} = N_{c_h} - type$,

- $q_h = (q_{1,h}, \ldots, q_{N_c,h})$

Let, $M = C(N_{c_h}, N_{c_h} - type)$ be the total number of possible combination of $\Big\{1, 2, \ldots, N_{c_h}\Big\}$ s.t $e_k^{c,type} = 1$, and, $S = \{S_1, S_2, S_M\}$ denotes the set of possible combinations. Compute

$$q_h^{c,\star}(S_m) = argmax\Big\{\sum_{k \in S_m} a_i.(q_k)^{\delta_{k,h}^{type}} - \alpha_k^{type} q_k \text{ subject to } \sum_k q_k = q_T \text{ and } 0 \leq q_k \leq q_{q_{max}}\Big\} \tag{16}$$

Compute $U(q_h^\star(S_m), \theta)$, for $m \in \{1, 2, \ldots M\}$. The optimal educational distribution is

$$q_h^\star(S_m) \mid U(q_h^\star(S_m) > U(q_h^\star(S_{m'}), \; \forall m' \neq m, \text{ with } q_i^\star = 0 \text{ if } i \notin S_m$$

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