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

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Abstract

This paper examines how gender, birth order, and ability shape within-household educational inequality, which accounts for 40% of the variation in educational attainment in developing countries. Using data from Benin, I find that in non-educated households, gender and birth order drive over two-thirds of educational disparities, while their influence decreases to one-third in households with college-educated parents. Furthermore, average inequality, measured by the range of children's education is twice as high among non-educated parents compared to college educated parents. I propose and estimate a structural model of educational attainment choices within-family. I demonstrate using the model that targeted educational cost reductions can eliminate gender and birth order effects without reducing average inequality in the sample. Additionally, removing barriers to school entry for all children reduces average inequality, although the gender effect remains persistent.

JEL classification: I220, I240, H520

Keywords: Education policy, Inequality, Equality of education opportunities, gender gap.

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1 Introduction

The trade-off between the number of children one chooses to have and the education 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 explains the relationship between the quantity and the average quality of children. Numerous empirical studies have provided support for this model in various contexts, consistently revealing a negative relationship between the number of children, and the educational attainment of those children. 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. However, in contexts where fertility can not be controlled by parents— low access to contraceptive methods— or when the quality of and access to public education system is poor or there is no clear understanding of the economic benefits of schooling, this trade-off seems to vanish (Montgomery (1995), Black et al. (2005), Maralani (2008)).

When we extend the analysis beyond the choice of the aggregate education of children to how it is distributed among children within a family, we evidence that, not only does the average change across households, but so does the variance of education. In addition, the variance is most likely non-zero for a majority of households when there are budget constraints and no or poorly enforced compulsory education laws. In such circumtances, 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 educational 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 are few 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 the analysis of the effectiveness of educational counterfactual scenarios in reducing inequality. 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 educational policies which target inequality due to gender or birth order effects.

This micro-level analysis of educational disparities is particularly relevant to the broader context of educational challenges in Sub-Saharan Africa, where lack of education remains a critical obstacle to development. Despite numerous reforms, the region continues to struggle with high illiteracy rates, significant educational inequality, and a substantial proportion of the world's out-of-school children (Unesco (2021)). While primary completion rates are approaching or exceeding 90% in most regions globally, Sub-Saharan Africa lags behind, with only two out of three children completing primary school (Unesco (2021)). Educational disparities are influenced by various barriers, which can be categorized into three types: situational (life circumstances), dispositional (personal attitudes), and institutional (structural conditions) (Unesco (2021)). An analysis conducted in Malawi, Nigeria, and Sierra Leone reveals that among secondary school-age adolescents who have never attended school, half cite dispositional barriers, such as a perceived lack of value or interest in education, as the main reason for being out of school. In Nigeria, institutional barriers like the lack of nearby schools also play a significant role. For those who have attended school but dropped out, dispositional barriers remain critical in Malawi but are less influential in Sierra Leone and Nigeria, where situational barriers, particularly financial constraints, prevent at least 40% of adolescents from returning to school. Additionally, marriage and pregnancy keep about 10% of adolescents, mostly girls, away from education. A crucial but often overlooked factor contributing to these disparities is within-family inequality, which accounts for approximately 40% of the variation in educational attainment in the developing world (Giannola (2023)).

Using this regional evidence of educational inequality as a foundation, this paper focuses on the specific context of Benin. Benin is an ideal location for this study for three main reasons: the non enforcement of compulsory education laws, the significant variability in educational attainment among individuals within the same household, and the observed disparities in educational opportunities based on gender and birth order. 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 educational resources

[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

parents have to distribute and the education attainment of the head of household. Taking that into account, I perform my analysis on households with different observed characteristics separately.

In the first part of the paper, I establish two key stylized facts about intra-household educational inequality. First, there is a non-linear, hump-shaped relationship between household-level mean and variance of education. Second, I decompose educational inequality into gender, birth order, and unobserved residual effects, finding that among households with non-educated heads and one child of each gender, over two-thirds of the average inequality is due to gender and birth order, while among college-educated parents, only one-third is due to these factors. Furthermore, average inequality, measured by the range of children's education is twice as high among non-educated parents compared to college educated parents. I then propose a structural model of household educational resources allocation to rationalize the observed inequality with budget constraints and parents' preferences. I estimate the model using the Simulated Method of Moments, and analyze diverse counterfactual scenarios in how they affect average inequality and share of gender and birth order in the average inequality. The first counterfactual (1) an education voucher reduces neither the shares of gender and birth effects nor the average inequality in the sample. The second counterfactual (2) which remove barriers to school entry for all children reduces the average inequality in the sample but does not reduce the shares of gender and birth order effects. The third counterfactual (3) a targeted education cost reduction eliminates the share of gender and birth order effects but does not change the average inequality in the sample.

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

Other relevant literature

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)) predict that quantity and quality of children are negatively related. This paper contributes to that strand of the literature by offering two

appendix of the paper.

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 implicit assumption of equal education for children in the same household.

This paper also contributes to the literature on within-household schooling decision, particularly factors influencing parents' distribution decision of education resources among siblings. A key determinant of these distribution decisions is the gender of the child and the gender composition of the household. 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 high-ability children and allocate more nonhuman capital to low-ability children (Becker and Tomes (1976), Dizon-Ross (2019), Giannola (2023)). When parents are compelled to invest in the nonhuman capital— for example inheritance in form of land or financial assets— 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. First, 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)). Second, this paper propose a household educational resources distribution model which 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 effects, and the innate abilities of individual children in influencing parental distribution decisions.

This paper also contributes to the literature on educational Kuznets curve theory (Londoño (1990) and Ram (1990), Thomas et al. (2003), Morrisson and Murtin (2013)). Previous studies have analyzed the relationship between the mean and variance of education using cross country data or within-country time series data. This paper contributes to that literature by analyzing the relationship between the mean and variance of education using within-country cross household data. Specifically, it shows that in Benin at the household level; the relationship mean-variance of education is inverted U shaped with the pick point located at around 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 correcting 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 inequality, such as gender and birth order.

2 Data Description and Definition of Key Variables

2.1 Sample and Data

In this section, I present the data used in this paper. I use data from the 2013 Population and Habitation Census data of Benin. The 2013 Population and Habitation Census data of Benin used in this paper provide information on 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. 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 condition on the sample is motivated by the goal to examine the reasons for providing equal education to all children, as opposed to the alternative of not educating any children. In

[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.

particular households with only non-educated children do not offer any information about the distribution of education resources which this paper aims to analyze. The resulting sample comprises approximately $90,000$ individuals and $\approx 33,000$ households, serving as the basis for further investigation. The sample description is as follows:

1. **Sample 0:** All households with children between 25-40 yrs old ($\approx 160,000$ households)
2. **Sample 1:** Households in sample 0 with at least 2 children between 25 and 40 years old. ($\approx$ 51,600 households)
3. **Sample 2:** Households in sample 1 with at least one educated child between 25 and 40 years old.($\approx$ 32,800 households)

I use sample 1 for stylized facts, estimation of the model, counterfactual analysis, and comparative statics, and sample 2 only for counterfactual analysis, and comparative statics.

2.2 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:

Within household inequality: Is the inequality in the education attainment of children within a given household. It is measured by the within-household range of children's education attainment for households with 2 children. For households with more than 2 children, it is measure by the standard deviation of education.

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: 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.

2.3 Descriptive statistics

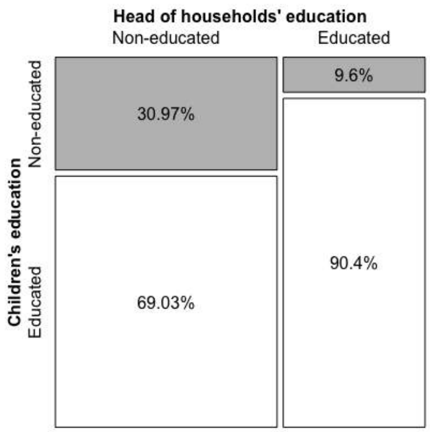
Table 1 displays the descriptive statistics for the key variables. First, among the observed offspring, 38% are female, their average education level is 8 years, with 80% having completed at least one year of education. Second, 40% of the heads of households have at least one year of education. About 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 1). These statistics provide suggestive evidence of both inter-generational educational mobility [4] and inter-generational educational persistence[5]. Third, regarding within-family inequality, the average within-household range in children's education is about 7 years with a maximum of 21 years of education. In addition the standard deviation of the within-family range of children's education is ≈ 4 years of education, signaling high variability in the with-household inequality across households.

Table 1: Descriptive Statistics

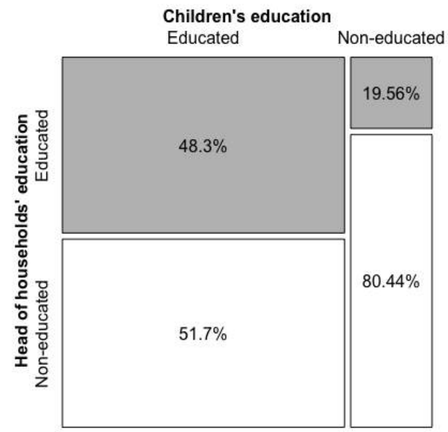
Statistic	**Mean**	**St. Dev.**	**Min**	**Max**
Age	29.452	3.993	25	40
Female	0.380	0.485	0	1
Years of education	7.760	5.802	0	21
At least one years of education	0.776	0.417	0	1
Range of children's education	6.821	4.873	0	21
Standard deviation of children's education	3.874	2.744	0.000	14.142
Educated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

[4]Children are more educated than their parents

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



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



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

Figure 1: Parents and children's education.

3 Empirical Evidence and Stylized Facts

3.1 Empirical Evidence

Empirical Evidence 1: *$\frac{2}{3}$ of the variation in education in the sample arises from disparities within households.*

I compute the average within-household variation in education and compare that to the overall variation in education in the sample. Furthermore, I examine how within and between-household variances in education are related. Let $q_h = (q_{h,1}, q_{h,2}, \ldots, q_{h,N_{c_h}})$ be the vector of children's educational attainment in household h with N_{c_h} children, and let $q = (q_1, \ldots, q_n)$ be the educational attainment of children in the sample.

$$Var(q) = Var\Big[\mathbb{E}[q|h]\Big] + \mathbb{E}\Big[Var(q|h)\Big].$$

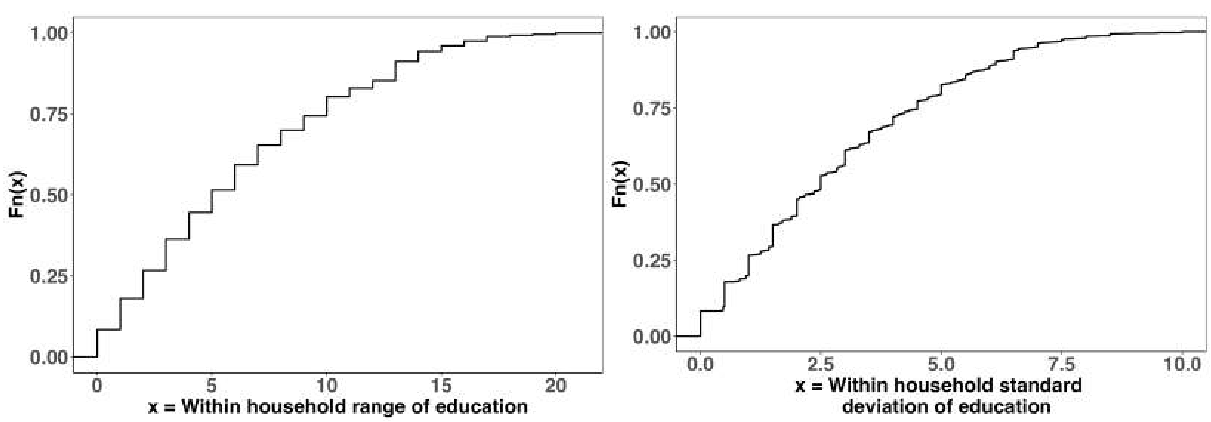
The variance of q is the sum of the average within-household variance $\big(\mathbb{E}\big[Var(q|h)\big]\big)$ and between $\big(Var\big[\mathbb{E}[q|h]\big]\big)$ household variation in q. The estimates of these quantities in my sample are the following:

$$\widehat{\mathbb{E}}\Big[s(q|h)\Big] = 22.63 \text{ and } s(q) = 33.66,$$

where $s(q_h)$ is the sample variance of children's education q_h in household h, $s(q)$ is the sample variance of education q in the whole sample, and $\widehat{\mathbb{E}}$ is the sample average. This indicates that $\frac{2}{3}$ 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 educational attainment. On the other hand, no within-household variation in education of children is associated with higher between households variance.

Empirical Evidence 2: *Within-household disparities in children's education is heterogeneous across households.*

This empirical evidence focuses on the extent of variation in 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 2 depicts the empirical distribution of the within-household range and standard deviation of the educational attainment of children. This figure 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.

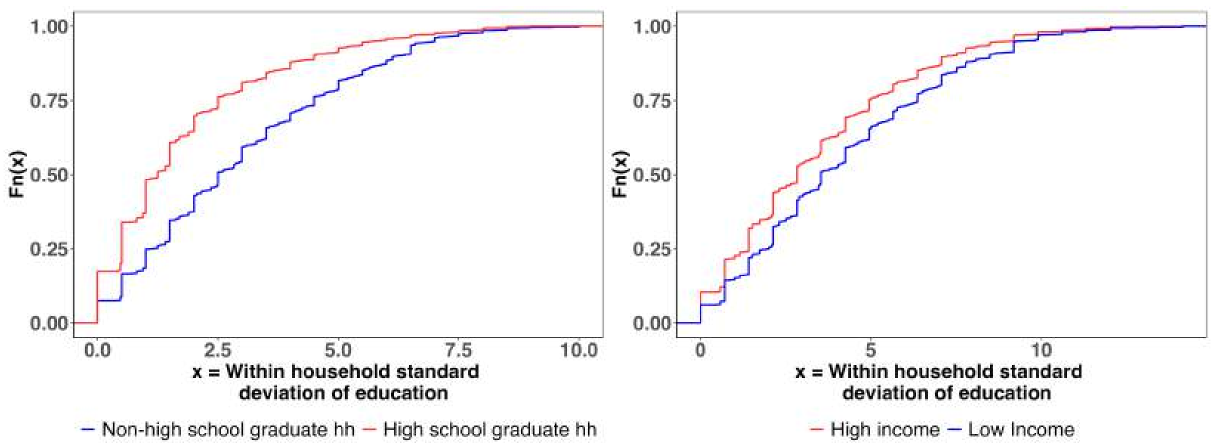


(a) Range (b) Standard Deviation

Figure 2: Empirical cdf of within-household range and standard deviation of education attainment of children.

These findings highlight the importance of considering household-level dynamics when addressing educational inequality and suggest that interventions aiming 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 3). 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.



(a) Parents Education (b) Household Wealth Index (HWI)

Figure 3: Distribution of inequality by socio-economic groups.

Empirical Evidence 3: *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 that 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. $q_h^{\max}$ is the maximum educational attainment of children in household h, $\sum_{i=1}^{N_c} 1\{q_i = q_h^{\max}\}$, is the proportion of children with that maximum within the household.

Table 2: Regression of withi- 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.

The estimation results in column (3)- (4) of Table 2 indicates that, on average, households with a 0.5 higher proportion of children attaining the maximum years of education within the household tend to have around 1.3 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 2). 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.

3.2 Stylized Facts

Stylized Fact 1: *The relationship between household-level mean and standard deviation of children's education is inverted U-shaped.*

The level of education attained by the head of a household has been found to be a significant factor associated with the level of inequality in children's educational attainment within that 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 4). This observation is particularly interesting given the hump-shaped relationship between inequality and average education of children (See Panel (b) of Figure 4). 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

[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

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-household inequality on average education of children, and parents' level of education, with a quadratic interaction between between this two variables.

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

where X_h include number of children, HWI, area of residence, religion and gender composition. Inequality$_h$ is the standard deviation of children's education in household h, $\bar{q}_h$ is the average education of children in household h, and hh_Educ$_h$ is the education of the head of household h. The estimation results in column (5)- (7) of Table 2 suggest that the negative dependence between parents' education and within-household 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.

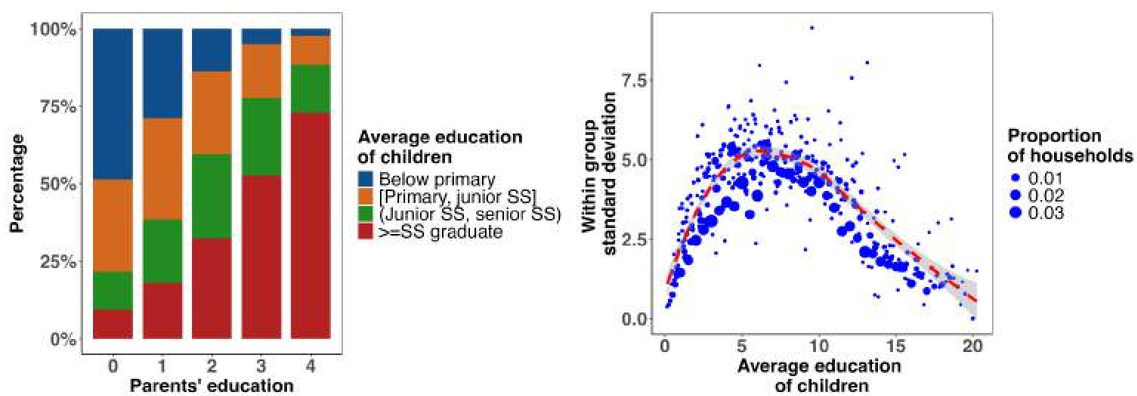


Figure 4: Distribution of average education attainment of children.

Stylized Fact 2: *Daughters with brothers and firstborn children receive on average less education compared to other children.*

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 5 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 that, 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.

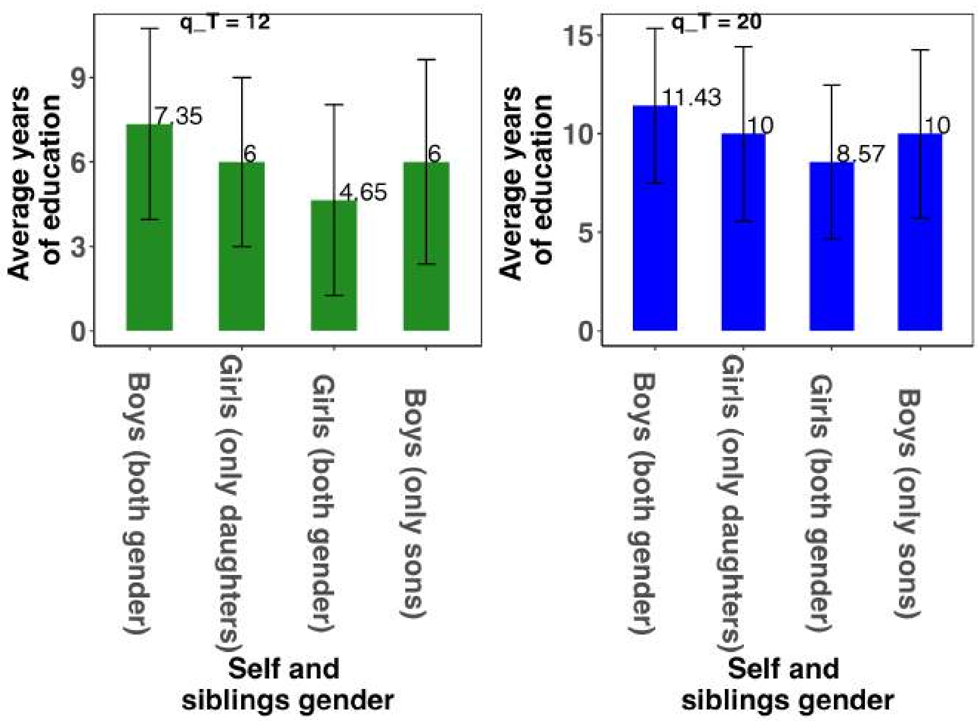


Figure 5: Average years of education by gender and households gender composition ($N_c = 2$)

Figure 6 allows similar analysis in terms of children's birth order after holding fix the number of children, and the within-household average years of education of children. The figure provides insight into the average years of education of first and second born children from two children households. In panel (a) of Figure 6, 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 6 suggest that there is disadvantage in birth order regarding the allocation of education quotas.

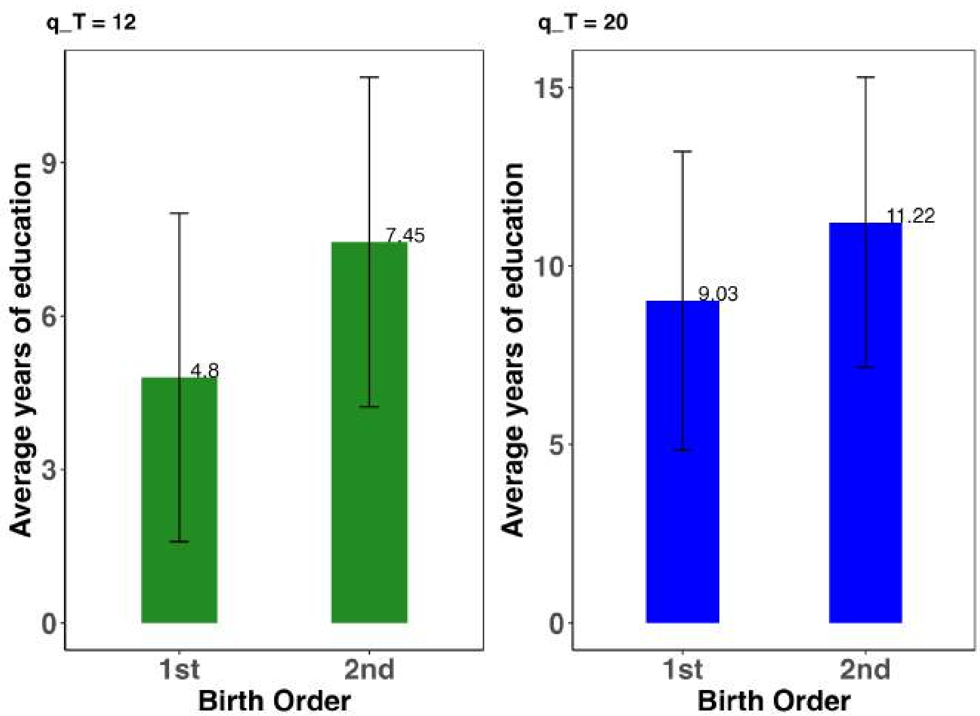
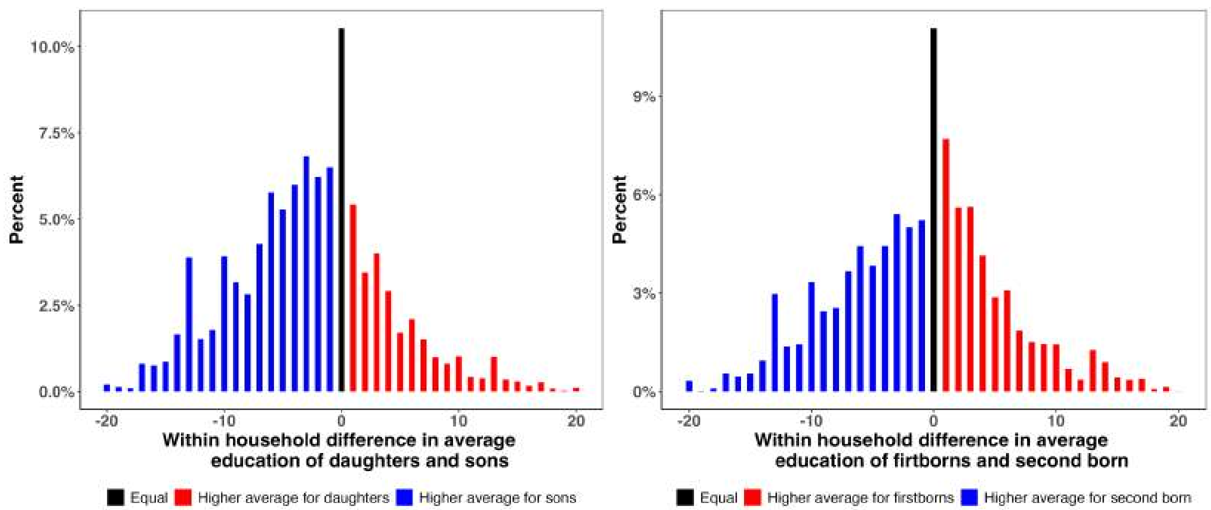


Figure 6: Average years of education by birth order ($N_c = 2$)

In summary, a child's gender, the gender of their siblings, and their birth order are key determinants of the years of education they receive. Despite taking into account observed 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 observed household and children characteristics (See the last two columns of Table 2). 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 7). 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.



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

Figure 7: Histogram of within-household difference in average education (Benin, 2013)

Stylized Fact 3-1: *Average within-household inequality in children's education is negatively related to parents' education. Among households with non-educated heads and one child of each gender, over two-thirds of the average inequality is due to gender and birth order, while among college-educated parents, only one-third is due to these factors.*

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. 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 unobserved abilities (or any unobserved factors affecting education resources distribution). The decomposition is conducted across various within-household average educational levels 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:

$$\text{Educ}_{i,h} = \beta_1 \text{Female}_{i,h} + \beta_2 \text{Firstborn}_{i,h} + \beta_3 \text{Female}_{i,h} \times \text{Firstborn}_{i,h} + \nu_h + \varepsilon_{i,h} \quad (3)$$

$$\text{Educ}_{i,h} = \beta_1 \text{Firstborn}_{i,h} + \nu_h + \varepsilon_{i,h} \quad (4)$$

where $\text{Educ}_{i,h}$ is the years of education of child i in household h, $\text{Female}_{i,h}$ is a gender indicator variable equal to 1 if child i in household h is a daughter, $\text{Firstborn}_{i,h}$ is a birth order indicator variable equal 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.

Table 3: Regression of children's education on their gender and birth order with household fixed effect by within-household total years of children's education ($N_c = 2$)

	(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.

The estimates from equation 3 and 4 are presented in Table 3 by average education of children and in Table 4 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 effects 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 effects. This change is due to the fact that part of the unobserved sources of inequality is muted by gender disadvantage.

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

	(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.

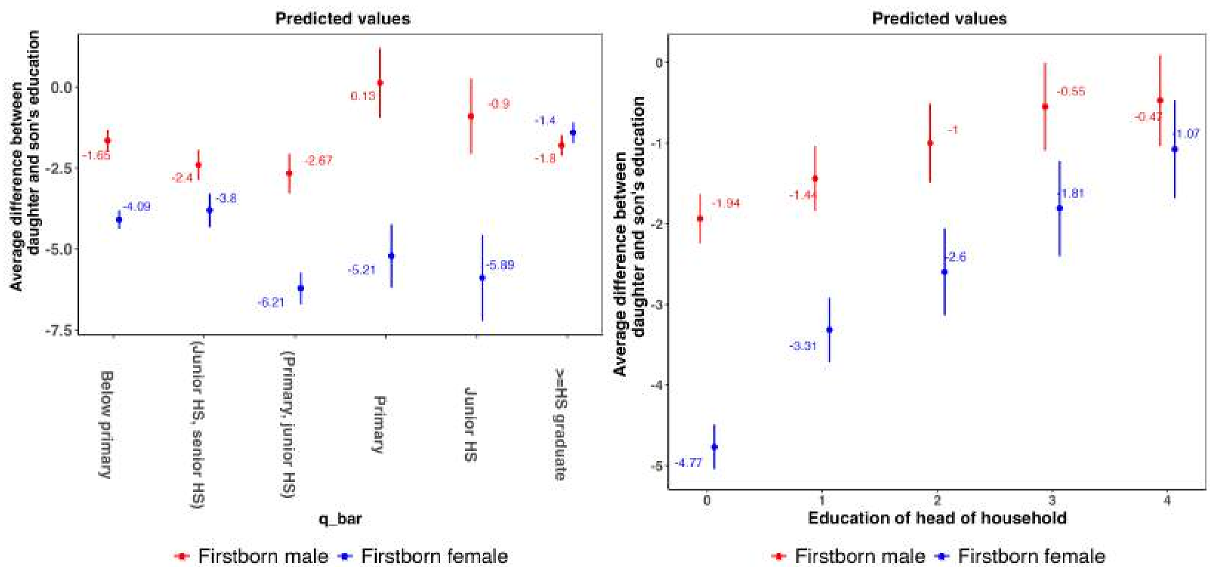
For the primary analysis, which focuses on households with just two adult children living at home, the reliability of the estimates shown in Tables 3 and 4 may be compromised. This unreliability stems from the incidental parameter problem, a consequence of having only two data points per household for the fixed effect regressions. To validate the initial findings, I use the following alternative regression for a more robust examination.

$$\Delta_{\text{daughter-son}}\text{Educ}_h = \beta_0 + \beta_1 \text{Firstborn\_daughter}_h + \varepsilon_h, \tag{5}$$

where $\Delta_{\text{daughter-son}}\text{Educ}_h$ is the average difference in the education of sons and daughters in household h, $\text{Firstborn\_daughter}_h$ is an indicator variable equals to 1 if the firstborn in household h is a daughter. The estimates are summarized in Figure 8. Figure 8 illustrates the mean disparity in educational attainment between daughters and sons, for households with a firstborn son and a firstborn daughter separately. 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), and are use to decompose the average absolute difference in children's education[8] by household's observable characteristics as follows:

$$\beta_0 + \beta_1 = \text{ average effect of gender } + \text{ average effect of birth order, and} \tag{6}$$

$$\beta_0 = \text{ average effect of gender } - \text{ average effect of birth order,} \tag{7}$$



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

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

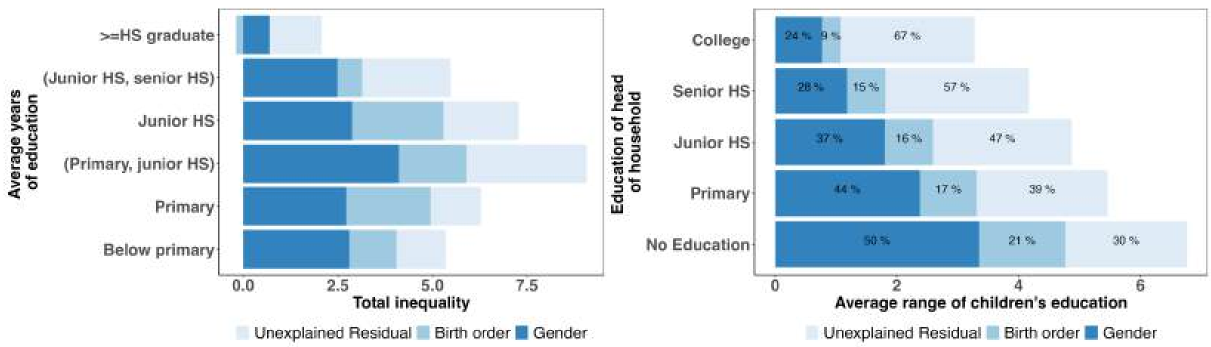
Figure 8: Effect of gender and birth order disadvantages on within-household inequality ($N_c = 2$)

I use equations 6 and 7 to get the average effect of gender and the average effect of birth order on within-family disparities in education. Note that in households with firstborn daughters, the same child is affected by both gender and birth order disadvantages. Given that $|\beta_0+\beta_1|$ is the average effects of gender and birth order on educational disparities within families, $E[\text{Range}|\text{household has a firstborn daughter}]-|\beta_0+\beta_1|$ is the unexplained residual[9]. I use these calculations to break down the average inequality found within-households into the three factors illustrated in Figure 9. Figure 9 displays how the average inequality is divided among gender effect, birth order effect, and differences in unobserved factors. It

[8] Let $q_h = (q_{1,h}, q_{2,h})$, and $\text{Range}_h = \max(q_h) - \min(q_h) = |q_{1,h} - q_{2,h}|$.

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

reveals 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 that there is variability in the degree of average inequality across different levels of children's average education and parents' education but also in the way it is broken down.



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

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

Figure 9: Inequality decomposition ($N_c = 2$)

Stylized Fact 3-2: *Intra-household educational inequality is present both at extensive and intensive margin. Compared to the extensive margin, the unexplained component has higher share in the average inequality for the intensive margin. The decrease in inequality by parents' education is mostly present in the extensive margin.*

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.

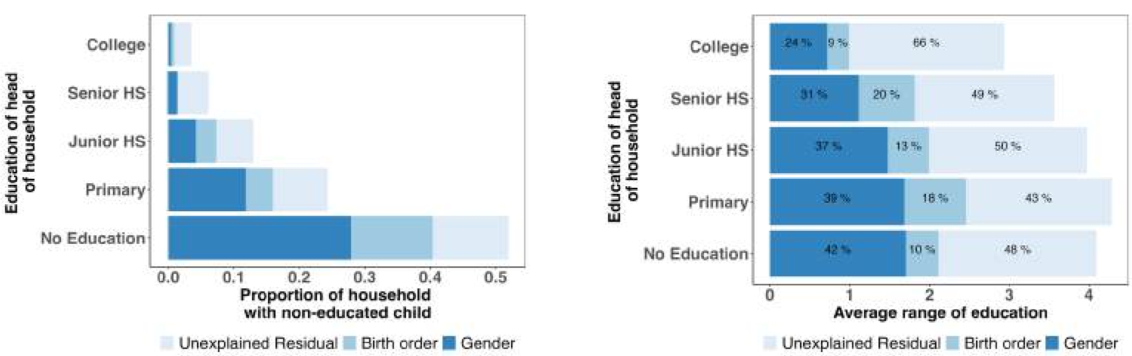
$$1\{Educ_{i,h} > 0\} = \beta_1 Female_{i,h} + \beta_2 Firstborn_{i,h} + \beta_3 Female_{i,h} \times Firstborn_{i,h} + \nu_h + \varepsilon_{i,h} \quad (8)$$

The estimates are presented in Table 5, and the decomposition of inequality at extensive and intensive margins is presented in Figure 10. 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 10 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.

Table 5: 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.



(a) Extensive Margin

(b) Intensive margin

Figure 10: Inequality decomposition as function of head of household's education ($N_c = 2$)

4 Structural Model of Educational Attainment Choice

4.1 Setup

The model I propose considers children as investment goods rather than simple 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 $\omega = \left(\omega_1, \ldots, \omega_{N_c}\right)$. 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' financial constraints, leading to limited educational opportunities for children. In particular, there is an unobserved type for parents which creates barriers to school entry for some of their children. These barriers include limited household resources that might not be sufficient to educate all children and labor demands in agricultural families that makes them keep certain children out of school to contribute to farming activities. The unobserved type dictates the percentage of uneducated children within the family. For households with two children, the unobserved type can take 2 possible value {High (0), or Low (1)}. The type "High" means high financial constraints and is associated with the presence of an uneducated child, whereas the type "Low" means low financial constraints and is associated with the absence of an uneducated child.

In the second stage of their decision, households decide on the distribution of q_T. This decision is function of their unobserved type combined with children's observed and unobserved characteristics. Specifically, each household is characterized by a type ν_h (their level of financial hardship). 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

$(q_1, \dots q_{N_c})$ of q_T, which maximizes the household's utility function.

$$\max_{q_i} U(q, \theta) \tag{9}$$

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

$U(.)$ 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 given.

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

I use a generalized utilitarian social welfare function to represent parents' utility function. This function incorporates a concave utility function derived from the education levels of each child. I chose this functional form because it better aligns with the observed mean-standard deviation curve, which differs from the one predicted by a linear utility function and more closely resembles a concave utility function from children's educational outcomes (see Figure **??**). Let $q_h = (q_{1,h}, \dots, q_{N_c,h})$ be the distribution of $q_{T,h}$ in household h. The utility function for households with 2 children has the following expression[10]:

$$U(q_h) = \nu_h \Big[\sum_{i=1}^{2} a_{i,h}.(q_{i,h})^{\delta_{i,h}^{\text{low}}} - \alpha_i^{\text{low}} q_{i,h} \Big] + (1-\nu_h) \Big\{ \sum_{i=1}^{2} \Big[e_{i,h}.\big(a_{i,h}.(q_i)^{\delta_{i,h}^{\text{high}}} - \alpha_i^{\text{high}} q_{i,h} \big) \Big] \Big\}, \tag{10}$$

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,
- $\nu_h = 1\{\text{T\_Educ}_h = 1\}$, is parents' level of financial constraints.
- $e_{i,h} = 1\{a_{i,h}.(q_T)^{\delta_{i,h}^{\text{high}}} - \alpha_i^{\text{high}} q_T > a_{j,h}.(q_T)^{\delta_{j,h}^{\text{high}}} - \alpha_j^{\text{high}} q_T\}$, $e_{j,h} = 1 - e_{i,h}$, $e_{i,h}$ and $e_{j,h}$ are indicator of whether not children i and j in household h have some education.
- $\delta_{i,h}^{\text{low}} = \delta(\text{gender}_{i,h}, \text{gender\_comp}_h) = \gamma - \theta_1^{low} \text{Female}_{i,h}(1 - \text{Female}_{j,h})$.
- $\delta_{i,h}^{\text{high}} = \gamma - \theta_1^{\text{high}} \text{Female}_{i,h}(1 - \text{Female}_{j,h})$.
- $\delta_{i,h}$ is the marginal benefit from giving a year of education to child i in household h.

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

- 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.

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

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

with, $b^{d,s} = \text{Female}_1.(1 - \text{Female}_2),\ \ b^{s,d} = (1 - \text{Female}_1).\text{Female}_2.$

The vector of parameters of interest is

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

The utility from providing a $q_{i,h}$ level of education for each child $[u_{i,h} = a_{i,h}.(q_{i,h})^{\delta_{i,h}^{\text{low}}} - \alpha_i^{\text{low}} q_{i,h}$ or $u_{i,h} = a_{i,h}.(q_i)^{\delta_{i,h}^{\text{high}}} - \alpha_i^{\text{high}} q_{i,h}]$ in the parents utility has two parts: the benefit and the 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 independent of gender and 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 parameter models the difference in educational attainment by gender, reflecting potential gender disadvantage that may exist within the household— as evidenced in Figure 5. The assumed functional form is designed to capture the idea that girls with brothers receive a penalty in the distributional 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 allows for differences in α across children's birth order to capture the monotonic increase in educational attainment as birth order advances as observed in Figure 6. To estimate the vector of parameter θ, I used an indirect inference approach. In particular a simulated method of moments. The procedure is outlined in the next section. The parameters are estimated for each level of education of parents.

4.3 Estimation and Inference Strategy

In this section, I provide an overview of the data moments used to estimate the key parameters in the model. I use two sets of moments for the parameters' estimation. First, the difference in average education between daughters and sons in households with one child of each gender and no uneducated children, while holding fixed parents' education and number of children; and the average educational attainment by birth order in households with children of the same gender only and no uneducated children, holding fixed the head of household's education and number of children. This moments provide data variations to estimate δ^{low} and $\alpha_{(i)}^{\text{low}}$ respectively.

The second set of moments includes the proportion of educated daughters and firstborn children in households with an uneducated child, while holding fixed parents' education and number of children. These moments help estimate parameters in δ^{high} and $\alpha_{(i)}^{\text{high}}$. Specifically, the proportion of educated firstborn children in households with only children of the same gender and one uneducated child estimates $\alpha_{(i)}^{\text{high}}$. The proportions of educated firstborn daughters and second born daughters are used to estimate $\theta_1^{\text{ds, high}}$ and $\theta_1^{\text{sd, high}}$, respectively.

For the rest of this section, 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 Y_h^1, Y_h^2, be the education of firstborn and second born children respectively. Additionally, let Z be a vector of observables, such as the education of the head of the household, the number of children (N_c), the aggregate education of children (q_T), 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.

Given the defined notations and functional form, the inference procedure proceeds as follows. First, I simulate H households, each with $N_c = 2$ children, possible gender composition (from $\{$ only sons, only daughters, firstborn son and second born daughter, firstborn daughter and second born son $\}$), number of educated children, and q_T. The simulated households' characteristics are drawn from of the empirical joint distribution of these variables. Second, for a fixed $\delta_{i,h}^{\text{high}}$, $\delta_{i,h}^{\text{low}}$, α_1^{high}, and α_1^{low}, I solve the household's maximization problem in equation 9 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 educational attainment of daughters in households with only daughters, where H^d is the number of simulated households with only daughters.

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

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

4. $S_s^i = s \times H^s$ 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 educational attainments represent the educational outcomes based on the given parameter values. I then take the average of the S_l^m 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 to 0.5 and estimating θ_1^{low} 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. For the inference on the parameters $(\alpha_{(t)}^{\text{low}})_{t=1}^{N_c}$ associated with birth order, the model and data moments are matched across different birth orders. This process entails normalizing $\alpha_{(N_c)^{\text{low}}}$ to 0 and estimating $(\alpha_{(t)}^{\text{low}})_{t=1}^{N_c-1}$ 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. For the parameters δ^{high}, and $(\alpha_{(t)}^{high})_{t=1}^{N_c}$, 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 $\hat{\mu}_l^d(\theta, Z)$ 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: Let T_{Educ} be the total number of educated children.

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

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

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

The corresponding sample objective function is the following expression:

$$\hat{Q}(\theta) = (\bar{Y}_{d,z}^d - \bar{Y}_{b,z}^d - (\hat{\mu}_{d,z}^d - \hat{\mu}_{b,z}^d))^2 + (\hat{m}_2 - \hat{\pi}_1)^2 + (\hat{m}_3 - \hat{\pi}_{fb,d})^2 + (\hat{m}_4 - \hat{\pi}_{sb,d})^2 + \sum_{l \in \{d,s\}} (\bar{Y}_{2,z}^l - \bar{Y}_{1,z}^l - (\hat{\mu}_{2,z}^l - \hat{\mu}_{1,z}^l))^2 \tag{11}$$

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

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

4.3.1 Estimation of G(.)

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

$$a_h \sim^{i.i.d} \text{Dirichlet}(\beta_1, \ldots, \beta_{N_{c_h}}) \text{ where, } a_h = (a_{1,h}, \ldots, a_{N_{c_h},h})$$

$(\beta_1, \ldots, \beta_{N_{c_h}})$ 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 $(\beta_1, \ldots, \beta_{N_{c_h}})$ using maximum likelihood method. The Dirichlet distribution seems to be a good fit for the distribution of relative ability (See Figure **??**).

5 Estimation Results and Counterfactual Analysis

5.1 Estimation Results

The estimates of θ are provided in Table 6 for households with $N_c = 2$ children, for non-educated and college educated parents.

Table 6: Estimates of $\hat{\theta}$, ($N_c = 2$)

	Non-educated parents					College educated parents	
	$\hat{\theta}_1^{\text{low}}$	$\hat{\alpha}_1^{\text{low}}$	$\hat{\theta}_1^{\text{ds, high}}$	$\hat{\theta}_1^{\text{sd, high}}$	$\hat{\alpha}_1^{\text{high}}$	$\hat{\theta}_1^{\text{low}}$	$\hat{\alpha}_1^{\text{low}}$
Estimates	0.0239**	0.0013	0.119**	0.13**	0.02**	0.00759**	0.00045
Standard errors	0.0014	0.0028	0.0004	0.0036	0.0013	0.0006	0.0012
Number of observations	6187		5083			942	

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

Result 1: *For parents without formal education and with high financial constraints, parents' perceived average utility at high school level of education is ≈ 14% higher for a second born child compared to firstborn child of the same gender.*

The estimate of the marginal educational cost difference between firstborn and second born children suggests that, on average, for parents without formal education and with high financial constraints, 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. Holding everything else equal, this cost difference translate into a utility gap of ≈ 14% for high school level of education.

Result 2: *For parents without formal education and with high financial constraints, perceived average utility at high school level of education is ≈ 41% higher for the second born son compared to the firstborn daughter.*

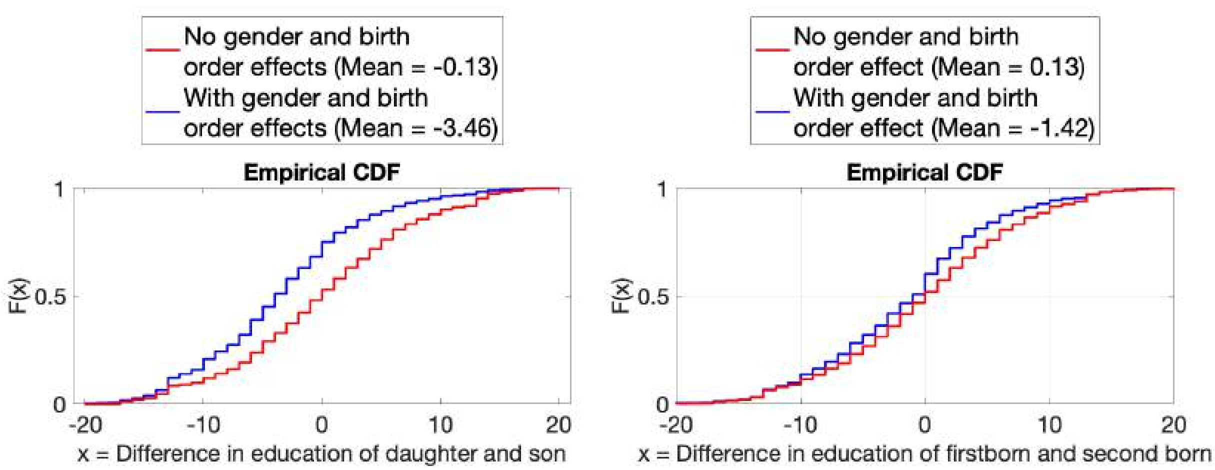
Among parents without formal education and high financial constraints, the marginal utility from an additional year of education is 33% high if given to a son compared to given to daughter. After factoring in birth order, these parents' perceived average utility at high school level of education is ≈ 40% higher for the second born son compared to the firstborn daughter. Their perceived average utility of graduating high school is ≈ 16% higher for the firstborn son compared to the second born daughter . Note that estimates for the extensive margin parameters ($\hat{\theta}_1^{\text{ds, high}}$, $\hat{\theta}_1^{\text{sd, high}}$ and $\hat{\alpha}_1^{high}$) are not provided for college-educated parents, as nearly all of them— approximately 98%— have only educated children.

Result 3: *Among parents with low financial constraints, the ones without formal education perceive a 6.2% higher utility on high school of education for sons compared to daughters, while for college-educated parents, the utility gap is approximately 3%.*

The parameter estimates for parents with low financial constraints indicate those without formal education perceive a 6.6% higher utility on graduating high school for sons compared to daughters, while for those with college education the difference is approximately 2.2%. The cost difference between providing a given level of education to firstborn children compared to second born is very small. For both non-educated and college-educated parents the estimates of the marginal costs different are not statistically different from 0 at 5% significance level. Parents' perceived average utility at high school level of education is $\approx$ .9% (resp. 0.3%) higher for a second born child compared to firstborn child of the same gender among non-educated parents (resp. college educated parents).

Result 4: *Without gender and birth order effects, the distribution of the average education difference between daughters and sons exhibits first-order stochastic dominance over the distribution in cases with such effects.*

In the absence of any gender and birth order effects, differences in education within a household between daughters and sons primarily result from variations in their individual unobserved abilities. If children's innate abilities are assumed to be distributed independently of gender and birth order, the average educational difference between daughters and sons, without considering gender or birth order effects, follows a symmetric distribution centered around 0. However, this distribution shifts towards the negative side in instances when gender and birth order disadvantages are present. In other words, without gender and birth order effects, the distribution of the average education difference between daughters and sons exhibits first-order stochastic dominance over the distribution in cases with such effects (see Figure 11).

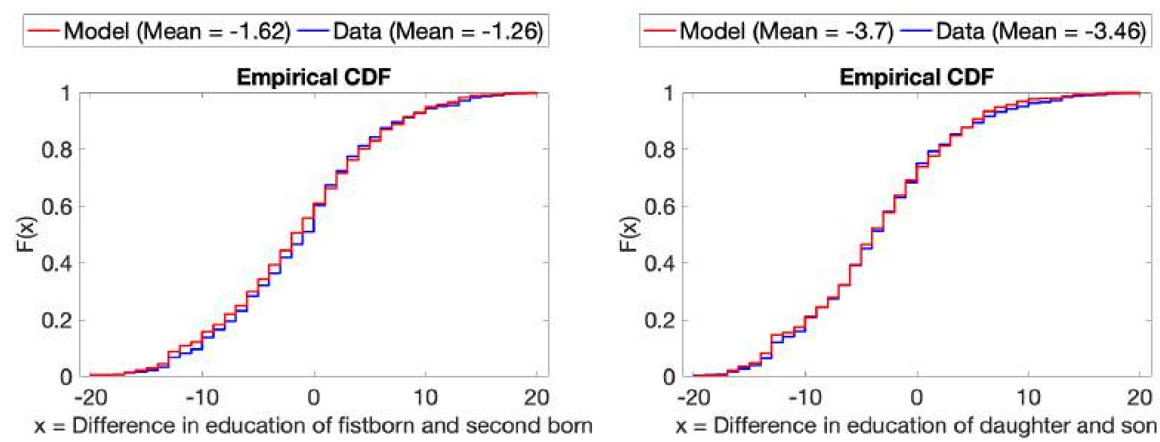


(a) Daughter v.s son (b) Firstborn v.s second born

Figure 11: Distribution of the difference in children's education ($N_c = 2$)

5.2 The Model's Fit

In this section, I access the fit of the model. Using the estimated parameters $\hat{\theta}$, I solve the household maximization problem, to obtain the optimal distribution $q_h^\star$ of q_{T_h} among children within each household h across a simulated sample of H households. I then compare $q^\star$ with the observed data to evaluate the model's fit. First, I compute the intra-household educational difference between daughters and sons' education, as well as between firstborn and second-born children using $q^\star$ for the simulated households. The empirical distributions of these within-household differences are compared with the ones from actual education attainment observed in the data. Figure 12 provides a visual comparison of the model's distributions with the observed data, showing a clear match. Second, I use $q^\star$ to derive targeted moments for estimation, alongside selected non-targeted moments. These analytical outcomes are summarized in Figure ??. It shows that there is no significant difference between the model and the data for all the targeted moments and most of the non-targeted moments as well.



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

Figure 12: Empirical distribution of key moments: Data vs. Model ((For non-educated parents))

5.3 Counterfactual Analysis

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

In this first counterfactual analysis, my primary goal is to assess how the unobserved source of inequality interact with the observed sources in the model. I do this by quantifying the additional ability needed to counterbalance educational inequality due to gender and birth order effects. First, I compute the extra ability needed by daughters and older siblings to offset the effect of gender and birth order on their educational attainment. In order to do that I solve the household maximization problem in equation 9 with (using $\hat{\theta}$) and without (setting $\theta = 0$) gender and birth order effects 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 quantities:

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 the presence of gender and birth order effects.
2. The change in inequality due to gender and birth order effects, by level of relative ability of the firstborn daughter.

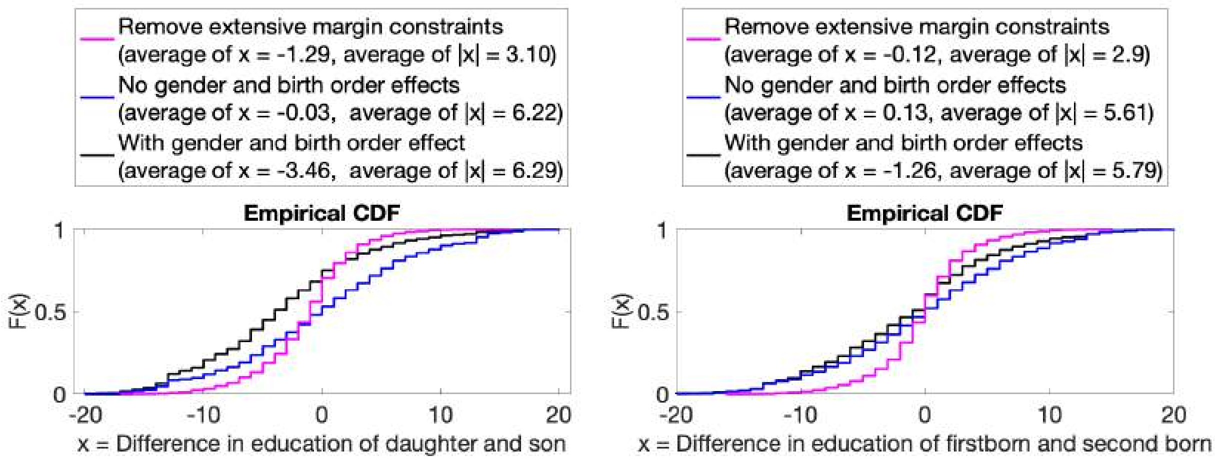
Figure **??** presents this first counterfactual analysis for non-educated and college educated parents with low financial constraints. It suggests three main conclusions. First, for the same ability draws, gender and birth order effects reduce the education attainment of the first born daughter by ≈ 4.6 years and 2.2 years 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).

5.3.2 Counterfactual 2: Education Policies

This counterfactual is analyzed only among non-educated parents only, and the outcomes are compared to college-educated parents' outcomes.

Remove Barriers to School Entry for all Children

The objective of this section is to examine the effectiveness of a counterfactual focusing on removing barriers to school entry, primarily addressing obstacles arising from parental decisions, to ensure that every child is enrolled in the school system. Figure 13 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 situations. The elimination of barriers to school entry reduces 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, after removing barriers to school entry for all children, second order stochastically dominates both the distributions with and without gender (and birth order) effects. This means that, compared to the situations there is no gender and birth order effects, removing barriers to school entry 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.



(a) Daughter v.s son (b) Firstborn v.s second born

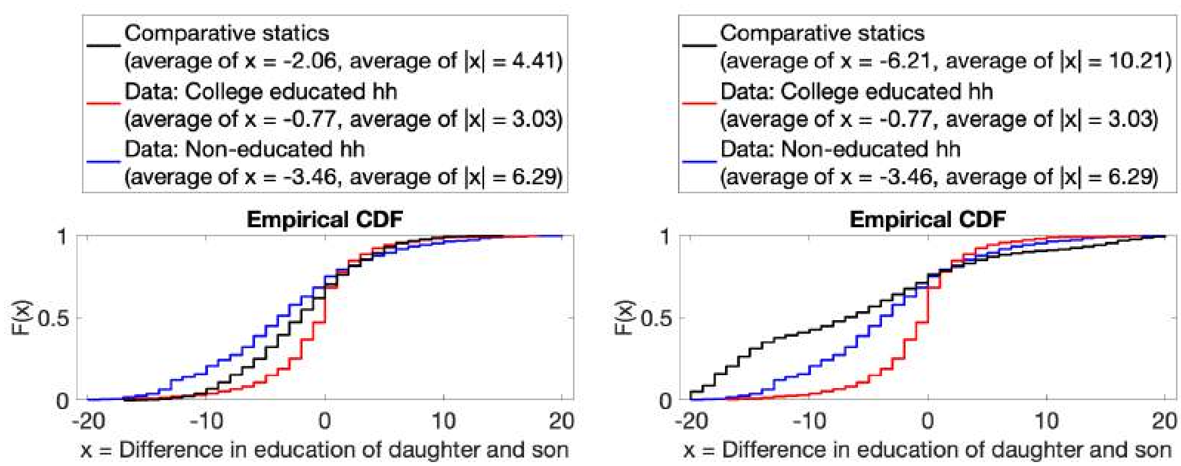
Figure 13: Distribution of the difference in children's education for non-educated parents ($N_c = 2$) [Observed vs. with compulsory education policy]

In summary removing barriers to school entry for all children reduces part of the gender and birth order effects on the within-household educational inequality. In addition, overall average within-household inequality is reduced by 50%. However, a significant share ($\approx 41\%$) of the average inequality is attributable to gender effect. In particular, it reduces the gender effect by 63% and birth order effect 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.

Education Voucher

This section looks at how increasing education resources for non-educated parents affects gender and birth order inequalities within households. Observed data evidence show that children of college-educated parents with two adult children have an average education level of 14.5 years, compared to 9.2 for children of non-educated parents. Additionally, nearly all college-educated parents have only educated children. In this section, I simulate an increase in the average education level of children from non-educated parents, raising it from about 9.2 to 14.5, along with implementing a compulsory education policy like the one described earlier. We then solve the household's optimization problem with this updated average and $\hat{\theta}$. Finally, I compare the new education differences between daughters and sons with the original disparities observed among non-educated and college-educated parents.

The results are depicted in Figure 14. The Figure suggests that this non-targeted increase in education resources combined with the removal of barriers to school entry for all children leads to a 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— almost as three times as high compared to college educated parents—. The gender effect is reduced by 40%— which is smaller than the reduction observed with the removal of the barriers to school entry alone in the previous section—. Overall average inequality reduced by $\approx 30\%$. That reduction is also smaller compared to the one we had when only barriers to school entry are removed. 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 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 gender effect among non-educated parents to the same level as college educated parents but did reduce overall average inequality.



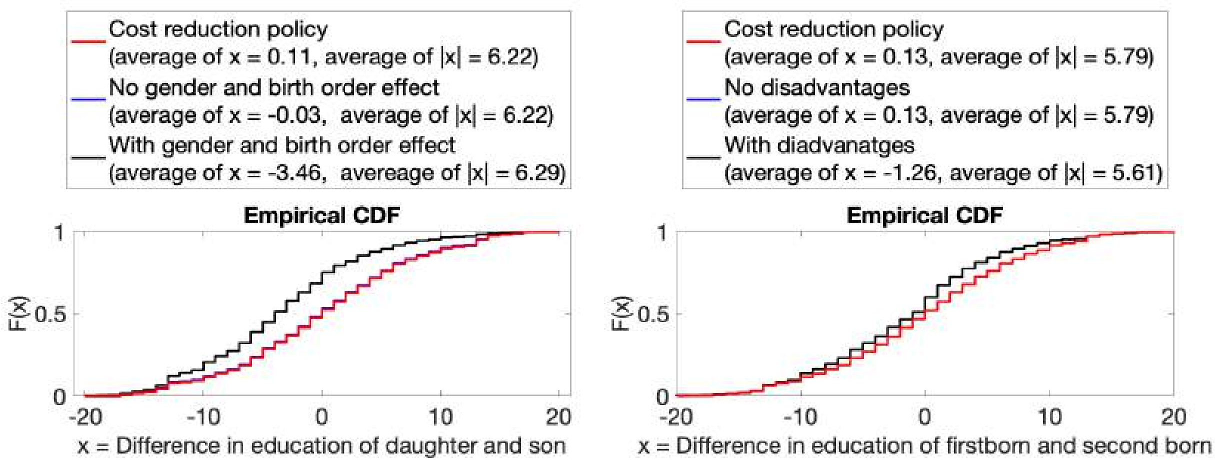
(a) Education voucher without barriers to school entry

(b) Education voucher with barriers to school entry for one child

Figure 14: Distribution of difference in daughter and son's education [for non-educated parents [observed and after an education voucher policy] and college educated parents]

Targeted Cost Reduction Policy

This section analyzed a calibrated 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 effects exist, even in the presence of such biases. Figure 15 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 there is gender and birth order disadvantages. 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.



(a) Daughter v.s son (b) Firstborn v.s second born

Figure 15: Distribution of the difference in children's education for non-educated parents ($N_c = 2$) [Observed vs. with targeted cost reduction policy]

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

Table 7: Summary of Education Policies Counterfactual

	Eliminate gender & birth order effects	Reduce overall inequality
Remove barriers to school entry (1) ✗	✓	
(1) + Education voucher	✗	✓
Remove gender & birth order disadvantages	✓	✗

6 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.

6.1 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 **??**. 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 ??). 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.

6.2 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.

7 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 as 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 effect, birth order effect, 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 for 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.

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