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Gender, age cohort, and household investment in child schooling

New evidence from sub-Saharan Africa

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Abstract: Sub-Saharan Africa continues to post one of the highest gender gaps in educational outcomes in the world. Gender gaps in educational outcomes might be attributed to an uneven allocation of household resources towards the schooling of boys and girls. In this paper, we interrogate this issue using individual-level data from Ghana. Methodologically, the paper explores two potential sources of gender bias: bias in the decision to enrol/keep boys and girls in school; and bias in the educational expenditure on boys and girls enrolled in school. Our findings are illuminating: gender bias in households' educational expenditure allocations arises mainly from the decision to enrol or not boys and girls in school, where an important pro-male bias exists. That is, households favour boys in their decision whether or not to enrol a child in school in Ghana. However, after enrolment, households tend to spend an equal amount on the schooling of both boys and girls. These findings have important implications for educational policy design, especially in the context of developing countries.

Key words: educational expenditures, gender bias, household, human capital

JEL classification: D13, I21, I22

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1 Introduction

Gender gaps in educational outcomes are still pervasive in the world, the incidence being disproportionately higher in sub-Saharan Africa (SSA) than in any other region in the world; in SSA, the gender parity index for educational outcomes stood at 0.74 in 2011 (UNESCO 2013). The existence of gender gaps in educational outcomes might be attributed to the fact that households tend to allocate more resources towards the schooling of boys (Aslam and Kingdon 2008). In this paper, we explore the validity of this statement using individual-level data.

A number of studies have explored the issue of gender bias in intra-household allocation of resources (see, for example, Deaton 1989; Gong et al. 2005), but only a few of these studies examine gender-differential treatments in households' educational expenditure (Aslam and Kingdon 2008; Kingdon 2005; Lancaster et al. 2003; Subramanian 1995; Subramanian and Deaton 1990, 1991). The current literature on gender bias is, however, not without limitations. First, much of the work on gender bias in intra-household educational expenditure allocation does not focus on countries in SSA,[1] even though SSA appears to be the region with the highest gender gaps in educational outcomes.

Second, due to the absence of individual-level data on expenditures in most cases, much of the existing work on the detection of gender bias in intra-household expenditure allocations has used household-level expenditure data (see Deaton 1997, for instance). These studies infer gender-differential treatment from an analysis of changes in the gender composition of a household and how these alter household consumption or expenditure patterns. This approach has, however, often failed to pick up gender bias in households' expenditure allocations even in cases where outcomes show the presence of gender bias—a situation that may be explained by the fact that aggregated household-level data mutes the detection of gender biases.[2]

The inability of earlier studies to identify gender bias in intra-household expenditure allocation has also been attributed to the use of an inappropriate estimation technique, namely the Engel curve method.[3] The current paper makes an important contribution to the literature by examining the issue of gender bias in intra-household allocation of educational resources using individual-level expenditure data for an SSA country. Further, we overcome the difficulties associated with the Engel curve technique by using a hurdle or two-tiered model to unravel the key sources of gender bias in households' educational expenditure allocations.

The empirical analysis of the study reveals the following results. First, the importance of both household income and household size in explaining educational expenditure allocations, with household income crucially determining both the probability of enrolling a child in school, especially in rural areas, and the amount spent on schooling a child after enrolment. Second, that

[1] Ogundari and Abdulai (2014), for example, analysed the determinants of households' education and health expenditures using a Nigerian household survey data set. The authors did not, however, provide evidence of gender bias in households' educational expenditures.

[2] See Ahmad and Morduch (2002), Jensen (2002), and Rose (1999) for explanations as to why the use of aggregated household-level data makes it difficult to detect gender bias.

[3] Kingdon (2005) opines that the failure of earlier studies to detect gender bias in intra-household allocation of resources is attributable to: first, the use of the Engel curve approach, which uses an incorrect functional form to model the mechanisms of bias; and second, the use of aggregate household-level data, which weakens the possibility of detecting gender bias.

urban locality is a positive predictor of both the probability of child school enrolment and how much is invested in the schooling of a child conditional on her being enrolled in school. Third, that female headship is a significant positive predictor of households' decision to enrol boys and/or girls in schools in both urban and rural areas. However, conditional upon enrolling boys and/or girls in school, male-headed households commit relatively more resources towards the schooling of children than female-headed households. This means that after *all* children are enrolled in school, children who live in households that are headed by males receive a higher educational expenditure allocation than their counterparts who live in households headed by females. This may reflect differences in the economic conditions of male- versus female-headed households. Finally, that educated parents are more committed towards the schooling of their children than uneducated parents.

Our evidence of gender bias in households' educational expenditure allocations is illuminating. In particular, our results suggest that gender bias arises mainly from the decision to enrol boys and girls in school. For instance, among children in the basic education school-going age cohort and beyond, an important pro-male bias exists in households' decision to enrol boys and girls in school but not in the conditional educational expenditure decision. That is, households discriminate across gender in their decision to enrol a child in school in Ghana. However, after enrolment, households tend to spend an equal amount on the schooling of both boys and girls. These findings have important implications for educational policy design, especially in the context of developing countries.

The rest of the paper proceeds as follows: Section 2 summarizes the related literature, Section 3 discusses the data and method of empirical analysis, Section 4 presents the study's empirical analysis, and Section 5 concludes.

2 Related literature

A large number of empirical studies on the drivers of household demand for education exist, focusing largely on educational outcomes such as child school enrolment and/or educational attainment (see, for instance, Connelly and Zheng 2003; Glick and Sahn 2000; Iddrisu 2014; Iddrisu et al. 2016; Rolleston 2011; Sackey 2007; Zimmerman 2001). For instance, Iddrisu et al. (2016) analyse whether the determinants of school progression differ across educational transitions using data from the latest wave of the Ghana Living Standards Survey (GLSS 6), conducted in 2012/13. The authors show that family resources such as parental education and household income crucially determine children's school participation. In particular, household income does not significantly influence *entry* into primary school, whereas children's *completion* of primary school depends significantly on household income. Gender differences in school participation are also observed but only with regard to secondary school enrolment. Rolleston (2011), using three waves of the Ghana Living Standards Survey (3, 4, and 5), previously established that household welfare, the gender of the child, and the parents' educational attainment significantly influence the decision to enrol a child, the gender effect being in favour of males.

An important body of literature specifically examines the determinants of households' educational expenditure. Examples are Aslam and Kingdon (2008), Glewwe and Patrinos (1999), Iddrisu et al. (2017), Ogundari and Abdulai (2014), Qian and Smyth (2011), and Tansel and Bircan (2006). The findings emerging from this strand of the literature suggest, broadly, that household resources—including financial and human resources—have a significant effect on households' educational expenditure. In particular, the evidence suggests that households with higher incomes and better-educated parents spend more on the education of their children. For instance, investigating the determinants of demand for private tutoring in Turkey on the basis of a household expenditure survey in 1994, Tansel and Bircan (2006) observed that households with higher incomes, households with higher parental education levels, and urban households allocate more resources to private tutoring of their children. This aligns with the results obtained by Qian and Smyth (2011). Ogundari and Abdulai (2014) employed household survey data from Nigeria to analyse the determinants of households' education and healthcare spending. They found that household income, household size, and the level of education of the household head positively and significantly drive households' decisions on whether to spend and how much to spend on educational and healthcare services. In addition, they observed that, relative to male-headed households, female-headed households tend to spend more on the education of household members and healthcare services.

In parallel, an impressive body literature examines the presence a gender-biased investment in child schooling. Gender discrimination in household expenditure on child schooling is broadly highlighted in these studies (see, for example, Aslam and Kingdon 2008; Chaudhuri and Roy 2006; Kingdon 2005; and Lancaster et al. 2003). Lancaster et al.'s (2003) study, for example, utilized two different data sets in India to detect gender bias in household educational expenditure. By applying the Engel curve methodology and a three-stage least squares estimation method, the authors found the presence of a significant gender-differential treatment in educational expenditure in underdeveloped rural India. Similarly, using both household-level and individual-level data derived from the Pakistan Integrated Household Survey 2001/02 and adopting the conventional Engel curve methodology as well as a hurdle model, Aslam and Kingdon (2008) found the presence of pro-male biases in both the enrolment decision and the decision on how much to spend (conditional on enrolment) on children in the middle and secondary school age ranges. However, for children in the primary school age group, the study established the presence of a pro-male bias in the decision whether to enrol sons and daughters in school only within the hurdle model framework; estimates from the conventional Engel curve methodology failed to detect bias in the educational expenditure allocation for children in the 5–9 age group.

Himaz (2009) used data from the second round of the Young Lives Survey 2006 in Andhra Pradesh, India, to examine the presence of boy bias in households' educational expenditures for children in the 5–19 age group. The study showed the presence of an important gender bias in household expenditure on child schooling and that this bias was in favour of boys. In line with this, Gong et al. (2005) and Li and Tsang (2003) established the presence of significant gender gaps in household educational spending in rural China. More recently, studies by Masterson (2012) for Paraguay and Saha (2013) for India have corroborated earlier findings on the existence of a significant gender bias in favour of boys in intra-household educational expenditure.

Despite the large number of studies on gender bias in intra-household educational expenditure allocation, this literature is limited in a number of respects. First, much of it does not focus on countries in SSA, even though SSA appears to be the region with the highest gender gaps in educational outcomes. Second, due to the absence of individual-level data on expenditure in most cases, much of the existing work on the detection of gender bias in intra-household expenditure allocation has used household-level expenditure data (see Deaton 1997, for instance). These studies attempt to infer gender-differential treatment by analysing how changes in the gender composition of a household alter household consumption or expenditure patterns. This approach has, however, often failed to pick up gender bias in households' expenditure allocations even in cases where outcomes show the presence of gender bias—a situation that may be explained by the fact that aggregated household-level data mutes the detection of gender biases (Kingdon 2005).

The inability of earlier studies to identify gender bias in intra-household expenditure allocation has been attributed to the use of an inappropriate estimation technique, namely the Engel curve method (Kingdon 2005). The current paper makes an important contribution to the literature by examining the issue of gender bias in intra-household allocation of educational resources using individual-level expenditure data for an SSA country. Further, we overcome the difficulties associated with the Engel curve technique by using a hurdle or two-tiered model to unravel the key sources of gender bias in households' educational expenditure allocation.

3 Data and method of empirical analysis

3.1 Data

In this paper, we use individual-level expenditure data on child schooling drawn from the latest wave of the Ghana Living Standards Survey (GLSS 6) conducted in 2012–2013 by the Ghana Statistical Service (GSS) with support from the World Bank. The GLSS 6 is a multidimensional household survey that collects a wide variety of household- and individual-level information, including detailed demographic characteristics of the population, education, health, employment and time use, migration, housing conditions, and household agriculture. The GLSS 6 collected data on 16,772 households and 72,372 individuals. Specifically, the survey collected information on the total educational expenditure on each individual per annum. The existence of these data provides an excellent opportunity to investigate the pattern of households' educational expenditure and their variation by the gender of the child.

Dependent variable

The dependent variable is the total annual educational expenditure for each individual (*Educexpend*). This consists of expenditure on school items—including registration and ongoing school fees, contribution to parent–teacher associations, uniforms and sports clothes, books and school supplies, transportation to and from school, food, board and lodging at school, extra classes, and in-kind expenses—for each individual who attended school in the previous 12 months. The average annual total educational expenditure on an individual aged 2–24 years in Ghana is 250 cedis (US$45), although annual spending is significantly higher in urban areas (about 455 cedis/US$82 per annum) than in rural areas (about 133 cedis/US$24 per annum). In terms of gender, the mean annual total educational expenditure does not differ significantly between boys and girls in Ghana (Table 1). However, across localities (i.e. rural versus urban) we observe that average annual educational expenditure on a boy is higher than on a girl, and this difference is sufficiently larger in rural areas than in urban areas.

Table 1: Mean educational expenditure allocations per child, locality and gender disaggregated (amounts are in GH₵)

	Urban	Rural	Ghana
Ghana	455.59	133.41	250.89
Boys	457.65	140.15	250.39
Girls	453.70	126.18	251.40

Source: authors' construction.

Explanatory variables

Based on the literature review exercise presented in the previous section, we find it relevant to include in our empirical estimations, as regressors, factors such as family background (which encompasses household welfare/income), the gender of the child, the educational experience and occupation of their parents, the gender of the household head, the size of the household, and the geographical location of the household (i.e. urban versus rural and/or regional). The rationale for the inclusion of the aforementioned regressors is that the positive effect of household income on households' educational expenditure is broadly established in the literature (see Qian and Smyth 2011; Tansel and Bircan 2006). Also, several studies show the importance of parental educational attainment in explaining households' educational expenditure on a child (see, for example, Qian and Smyth 2011; Tansel and Bircan 2006). Further, the significance of parents' occupation in a model of household educational expenditure is not in doubt (see Tansel and Bircan 2006).

Moreover, Ogundari and Abdulai (2014) show the importance of household size in determining household educational expenditure. In addition, the existing literature suggests that, relative to male-headed households, female-headed households tend to spend more on the education of household members. At the same time, some studies depict a stronger link between households' educational expenditure and the geographical location of the household: in particular, households in urban areas spend more resources on educating their children than rural households (Glewwe and Patrinos 1999). More importantly, we examine gender bias in households' educational expenditure allocations. Gender discrimination against girls in household expenditure on schooling is widely highlighted in the literature (see Aslam and Kingdon 2008; Himaz 2009). For instance, in rural China, Gong et al. (2005) show that parents prefer to educate their male children rather than female children and that expenditure on a boy who attends school is greater than that for a school-going girl of the same age. Therefore, the explanatory variables considered in this paper are: the logarithm of household income and its square, the logarithm of household size, the gender of a child, and a vector of other control variables including the educational experience of a child's parents, the gender of the household head, the occupation of a child's parents, a dummy for urban residence, and regional dummies (see Table 2 for a description of these variables). Given the nature of the explanatory variables considered in this study, we do not expect endogeneity to be a problem in our estimations.

Table 2: Descriptive statistics of regression variables

Variable	Description	Mean	S.D.	Range
Educexpend	Continuous: measures a household's total annual expenditure on a child's schooling	250.89	648.18	0–57530
lnrealpc	Continuous: the logarithm of households' total annual consumption expenditure per adult equivalent	1.51	0.77	-2.23–4.64
lnrealpc2	Continuous: the square of 'lnrealpc' and it is meant to capture the non-linearity in the effect of household income	2.87	2.43	1.31e-07–21.50
lnhsize	Continuous: captures the logarithm of household size	1.78	0.50	0–3.37
Urban	Binary: measures the geographical location of a household and assumes a value of 1 if a household is located in an urban area and 0 otherwise	0.37	0.48	0–1
Head_male	Binary: captures the gender of the head of the household and assumes a value of 1 if the head is a male and 0 otherwise	0.02	0.13	0–1
Father's_educ	Categorical: measures the highest educational attainment of a child's father. It takes a value of 0 for 'no education', 1 for 'primary', 2 for 'junior high school', 3 for 'senior high school', and 4 for 'post-senior high school' as a child's father's highest educational attainment. A value of 5 is assigned for 'don't know'.	1.57	1.59	0–5
Mother's_educ	Categorical: measures the highest educational attainment of a child's mother. It takes a value of 0 for 'no education', 1 for 'primary', 2 for 'junior high school', 3 for 'senior high school', and 4 for 'post-senior high school' as a child mother's highest educational attainment. A value of 5 is assigned for 'don't know'.	0.85	1.33	0–5
Male	Binary: measures the gender of a child and takes a value of 1 if 'male' and 0 otherwise	0.50	0.50	0–1
Regional dummies				
Western	Binary: measures the geographical location of a household and assumes a value of 1 if the household is located in the 'Western Region' and 0 otherwise.	0.10	0.29	0–1
Central	Binary: measures the geographical location of a household and assumes a value of 1 if the household is located in the 'Central Region' and 0 otherwise.	0.09	0.28	0–1
Greater Accra	Binary: measures the geographical location of a household and assumes a value of 1 if the household is located in the 'Greater Accra Region' and 0 otherwise.	0.08	0.27	0–1
Volta	Binary: measures the geographical location of a household and assumes a value of 1 if the household is located in the 'Volta Region' and 0 otherwise.	0.09	0.29	0–1
Eastern	Binary: measures the geographical location of a household and assumes a value of 1 if the household is located in the 'Eastern Region' and 0 otherwise.	0.10	0.29	0–1
Ashanti	Binary: measures the geographical location of a household and assumes a value of 1 if the household is located in the 'Ashanti Region' and 0 otherwise.	0.10	0.30	0–1
Brong Ahafo	Binary: measures the geographical location of a household and assumes a value of 1 if the household is located in the 'Brong Ahafo Region' and 0 otherwise.	0.10	0.30	0–1
Northern	Binary: measures the geographical location of a household and assumes a value of 1 if the household is located in the 'Northern Region' and 0 otherwise.	0.14	0.35	0–1
Upper East	Binary: measures the geographical location of a household and assumes a value of 1 if the household is located in the 'Upper East Region' and 0 otherwise.	0.10	0.29	0–1
Upper West	Binary: measures the geographical location of a household and assumes a value of 1 if the household is located in the 'Upper West Region' and 0 otherwise.	0.12	0.32	0–1

Source: authors' construction.

3.2 Method of empirical analysis

Kingdon (2005) proffered two possible reasons for the inability of earlier studies to detect gender bias in household expenditure allocation: first, that they used the incorrect functional form to model the mechanism of bias—the Engel curve approach;[4] second, that the use of aggregated household-level data dampens the detection of gender bias. Regarding the first issue, Kingdon (2005) argues compellingly that the Engel curve approach estimates a single expenditure equation that encompasses two different mechanisms of bias, and assigns an equal weight to the two. Gender bias in household expenditure on a given commodity may arise from two sources: (1) the household's decision on whether to spend anything on a given commodity—the 'binary decision' (zero versus positive expenditure); (2) the household's decision on *how much* to spend conditional on spending a positive amount—the 'conditional expenditure decision'. Averaging across these two possible sources of bias (as is implicit in the Engel curve approach) may thin out biases if gender bias is present through only one channel rather than both, or if the biases in the two channels are in opposite directions (Aslam and Kingdon 2008). For example, suppose that a pro-male bias exists in households' first decision—households are more likely to spend a positive amount on the education of boys than girls (i.e. enrolment decision)—but that a pro-female bias is present in households' second decision (the conditional expenditure decision) such that, conditional on enrolment, households spend more on the schooling of girls than boys. By averaging across these two divergent channels, the Engel curve approach may not pick up any gender bias even though there is a pro-male bias in the enrolment decision and pro-female bias in the conditional decision.

To overcome the methodological challenges associated with the Engel curve method, Wooldridge (2002) proposed the use of hurdle models (or two-tiered models) in models associated with corner solution outcomes. Hurdle models model households' expenditure decisions in two steps, thus separating the initial decision of $y = 0$ from the decision of *how much* y is, given a positive y. Proposed originally by Cragg (1971) and an improvement on Tobit models, hurdle models offer a great way to model the pattern of households' expenditure on commodities. Hurdle models are two-tier models because the 'hurdle' or first tier is the decision whether to choose positive spending or not ($y = 0$ *versus* $y > 0$) and the second tier is the decision *how much* to spend conditional on spending a positive amount ($y \mid y > 0$). As a result, it allows for the analysis of the two decisions separately—i.e. the binary and the conditional expenditure decisions—and thus highlights the two potential channels of bias in the intra-household allocation of resources. A simple hurdle model for a corner solution variable can be written as follows:

$$\mathbf{P}(y = 0|\boldsymbol{x}) = \mathbf{1} - \boldsymbol{\Phi}(\boldsymbol{x\gamma}) \qquad (1)$$

$$\log(y) \,|(\boldsymbol{x}, y > 0) \sim \text{Normal}\,(\boldsymbol{x\beta}, \sigma^2) \qquad (2)$$

where y is the share of a household's budget that is spent on education, $\boldsymbol{x}$ is a vector of explanatory variables, and $\boldsymbol{\gamma}$ and $\boldsymbol{\beta}$ are the parameters to be estimated, whereas σ is the standard deviation of w. The first equation, equation (1), shows the probability that y is zero or positive, while equation

[4] The Engel curve approach fits ordinary least squares (OLS) equations of the absolute education budget share on the sample of all households (including those with zero education expenditure). However, the application of OLS in models where the dependent variable is censored (e.g. the presence of a large proportion of households that report zero expenditure) yields parameter estimates that are biased downwards (see Deaton 1997). As an alternative to the OLS specification, Tobit models (James Tobin 1958) were proposed for use in models associated with corner solution outcomes. However, like the OLS specification, Tobit models assume that a single mechanism determines the choice between the zero-versus-positive ($y = 0$ *versus* $y > 0$) expenditure decision *and* the decision how much to spend conditional on choosing a positive amount in the former mechanism ($y \mid y > 0$) (see Deaton 1997; Wooldridge 2002). In particular, $\partial P(y > 0|x)/\partial x_j$ and $\partial E(y|x, y > 0)/\partial x_j$ are restricted to the same sign.

(2) dictates that, conditional on $y > 0$, $y|x$ follows a lognormal distribution.[5] If we assume $w = 1[y > 0]$ and use

$$f(y|\boldsymbol{x}) = \mathbf{P}(w = 0|\boldsymbol{x})f(y|\boldsymbol{x}, w = 0) + \mathbf{P}(w = 1|\boldsymbol{x})f(y|\boldsymbol{x}, w = 1) \tag{3}$$

we get

$$f(y|\boldsymbol{x}) = \mathbf{1}[y = 0][\mathbf{1} - \boldsymbol{\Phi}(\boldsymbol{x\gamma})] + \frac{\mathbf{1}[y > 0]\boldsymbol{\Phi}(\boldsymbol{x\gamma})\phi\left[\frac{\{\log(y) - \boldsymbol{x\beta}\}}{\sigma}\right]}{y\sigma} \tag{4}$$

since $\mathbf{P}[y > 0|\boldsymbol{x}] = \boldsymbol{\Phi}(\boldsymbol{x\gamma})$ and $\phi\left[\frac{\{\log(y) - \boldsymbol{x\beta}\}}{\sigma}\right]/(y\sigma)$ is the density of a lognormal random variable. However, a more appropriate way to express the density for maximum likelihood analysis is

$$f(y|\boldsymbol{x}; \boldsymbol{\theta}) = [\mathbf{1} - \boldsymbol{\Phi}(\boldsymbol{x\gamma})]^{1[y=0]}\{\frac{\boldsymbol{\Phi}(\boldsymbol{x\gamma})\phi\left[\frac{\{\log(y) - \boldsymbol{x\beta}\}}{\sigma}\right]}{y\sigma}\}^{1[y>0]} \tag{5}$$

for $y \geq 0$. If no restrictions are placed on $\boldsymbol{\gamma}$, $\boldsymbol{\beta}$, and σ^2, then the MLEs can be obtained easily: the log-likelihood function for observation $\boldsymbol{i}$ is

$$\begin{aligned}\ell_i(\boldsymbol{\theta}) = \mathbf{1}[y_i = 0]\log[\mathbf{1} - \boldsymbol{\Phi}(\boldsymbol{x\gamma})] + \mathbf{1}[y_i > \mathbf{0}]\{\log \boldsymbol{\Phi}(\boldsymbol{x_i\gamma}) - \log(y_i) - \frac{1}{2}\log(\sigma^2) \\ - \frac{1}{2}\log(2\pi) \\ - \frac{\frac{1}{2}[\log(y_i) - \boldsymbol{x_i\beta}]^2}{\sigma^2}\}\end{aligned} \tag{6}$$

The MLE of $\boldsymbol{\gamma}$ is the probit estimator using $w = 1[y > 0]$ as the binary response. The MLE of $\boldsymbol{\beta}$ is simply the OLS estimator from the regression of $\log(y)$ on $\boldsymbol{x}$ using only those observations for which the educational expenditure is positive ($y > 0$). A consistent estimator of $\hat{\boldsymbol{\sigma}}$ is the usual standard error from this regression. Our conditional assumption that $y > 0$ implies that log(y) follows a classical linear model, and hence the model can be estimated simply.

The empirical analysis in this paper is therefore carried out within the framework of the hurdle model. As mentioned earlier, the hurdle model offers an opportunity for an in-depth examination of the correlates of households' expenditure on commodities and, more importantly, for the investigation of gender differences in the within-household allocation of resources. In order to test the relative soundness of the hurdle model in detecting gender biases associated with household resource allocations, we also estimate an unconditional OLS (conventional Engel curve) equation of educational expenditure.[6] Specifically, therefore, the paper estimates: (i) a probit equation of the

[5] The dependent variable in the conditional expenditure equation is assumed to follow a lognormal distribution, since its distribution is skewed (see Figure A1 in the Appendix). By taking the log-transformation of the dependent variable, the distribution becomes more normal (see Figure A2). This approach fits the model better.

[6] See Aslam and Kingdon (2008) for the theoretical exposition of the conventional Engel curve model.

binary decision whether or not the household spends a positive amount on the education of an individual; (ii) a conditional OLS equation of the logarithm of household expenditure on the education of an individual; and (iii) an unconditional OLS (conventional Engel curve) equation of the household's educational expenditure on an individual.

The empirical analysis in this paper is conducted at the individual level. In line with the current educational system in Ghana (see Iddrisu et al. 2016), we estimate the regression for children in the following age cohorts: 2–24 years, 2–5 years, 6–12 years, 13–15 years, 16–18 years, and 19–24 years. For each age cohort, we estimate the model for the full (Ghana) sample and for a sub-sample of rural and urban dwellers.

4 Empirical results

This section presents the main empirical results of this paper. We examine the presence (or otherwise) of gender-differential treatment in households' child schooling expenditure by exploiting the important property of hurdle models and an individual-level expenditure data set. Our hurdle model estimates are, however, compared with estimates from an unconditional OLS (conventional Engel curve) model. In this way, the estimates fit both a conventional Engel curve model and a hurdle model using individual-level data.

As mentioned earlier, we present the results of six age cohort estimations using both a hurdle model and the conventional Engel curve approach for different data samples (Ghana sample and rural-versus-urban sub-samples). The locality-disaggregated samples allow us to examine the presence of locality-based differences in expenditure allocations among households.

The empirical results of the study are presented in Tables 3–8. Table 3 presents the baseline results (*all* children in the effective school-going age cohort: 2–24 years) for the full (Ghana) sample and the locality-disaggregated samples (urban and rural). Tables 4, 5, 6, 7, and 8 report, respectively, the results for children in the pre-primary school-going age cohort (2–5 years), the primary school-going age cohort (6–12 years), the junior high school-going age cohort (13–15 years), the senior high school-going age cohort (16–18 years), and the post-senior high school-going age cohort (19–24 years).

In each table, the results are organized as follows: the results of the unconditional OLS (conventional Engel curve) estimation are presented in column (a), column (b) reports the results of a probit of a positive educational expenditure, and column (c) the conditional OLS of the natural logarithm of budget share of education.

The discussion of the empirical results of the paper proceeds with the discussion of the results from the conventional Engel curve estimations (column (a) in each table), followed by a discussion of the results from the hurdle model estimations (columns (b) and (c) in each table).

Table 3: OLS, probit, and conditional OLS, full, and locality-disaggregated samples, 2–24 age cohort estimation

	Model 1 (Full sample)			**Model 2 (Urban sample)**			**Model 3 (Rural sample)**		
	Educexpend	**Anyexpend**	**Ln_Educexpend**	**Educexpend**	**Anyexpend**	**Ln_Educexpend**	**Educexpend**	**Anyexpend**	**Ln_Educexpend**
	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)
VARIABLES	Coef.	ME	Coef.	Coef.	ME	Coef.	Coef.	ME	Coef.
lnrealpc	-43.73	0.19***	0.71***	4.35	0.10	1.09***	28.43**	0.14*	0.64***
	(-1.64)	(2.82)	(8.52)	(0.05)	(0.68)	(6.95)	(2.53)	(1.75)	(5.52)
lnhsize	66.68***	0.39***	0.07*	105.48***	0.47***	0.10**	31.25***	0.33***	0.03
	(7.34)	(12.87)	(1.79)	(5.81)	(10.37)	(2.14)	(4.17)	(7.94)	(0.59)
Male	53.21***	0.61***	0.13***	43.56	0.46***	0.07	62.28***	0.72***	0.19***
	(3.33)	(18.00)	(3.62)	(1.20)	(8.95)	(1.45)	(6.84)	(15.92)	(3.69)
Head_male	-78.58***	-1.17***	0.75***	-59.68	-0.86***	0.76***	-80.76***	-1.45***	0.80***
	(-3.22)	(-15.96)	(6.25)	(-1.23)	(-8.20)	(5.64)	(-4.80)	(-13.57)	(3.48)
Urban	97.93***	0.21***	0.74***						
	(10.30)	(5.93)	(19.18)						
Constant	-146.58***	-0.70***	2.29***	-290.72***	-0.31	2.57***	-77.77***	-0.65***	2.39***
	(-6.87)	(-8.15)	(23.50)	(-3.59)	(-1.51)	(12.40)	(-5.31)	(-6.22)	(18.61)
Regional dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Other controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adj.R-sq	0.0636		0.441	0.0449		0.360	0.0887		0.279
Observations	7,951	7,951	7,951	3,516	3,516	3,516	4,435	4,435	4,435

Notes: robust t-statistics in parentheses; Male captures the sex of a child and the base category is ‘female’; Head_male captures the sex of a household head and the base category is ‘female’; Urban is a dummy for urban locality and the base group is ‘rural’; Regional dummies includes all the 10 regions of Ghana apart from ‘Upper West’, which is used as the reference category; Other controls included in the estimation are: (i) parental educational attainment, its base category being ‘no education’, and (ii) the square of the log of household income per capita (lnrealpc2); ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Source: authors’ construction.

Table 4: OLS, probit, and conditional OLS, full, and locality-disaggregated samples, 2–5 age cohort estimation

	Model 1 (Full sample)			**Model 2 (Urban sample)**			**Model 3 (Rural sample)**		
	Educexpend	**Anyexpend**	**Ln_Educexpend**	**Educexpend**	**Anyexpend**	**Ln_Educexpend**	**Educexpend**	**Anyexpend**	**Ln_Educexpend**
	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)
VARIABLES	Coef.	ME	Coef.	Coef.	ME	Coef.	Coef.	ME	Coef.
lnrealpc	-38.25	0.90***	0.99***	-11.53	1.32**	1.22*	10.38	0.94***	0.84*
	(-0.99)	(3.84)	(2.95)	(-0.09)	(1.99)	(1.69)	(0.57)	(3.55)	(1.94)
lnhsize	33.95	-0.16	0.33***	32.52	-0.40	0.25	14.09	-0.18	0.37**
	(1.50)	(-1.13)	(2.74)	(0.54)	(-1.31)	(1.38)	(1.06)	(-1.09)	(2.21)
Male	9.43	-0.12	0.14	15.09	0.01	-0.03	10.72	-0.19	0.30*
	(0.49)	(-0.91)	(1.27)	(0.35)	(0.03)	(-0.19)	(0.86)	(-1.22)	(1.95)
Urban	104.66***	-0.01	1.04***						
	(4.60)	(-0.05)	(8.78)						
Constant	-84.53*	0.34	0.81**	-47.13	5.43***	2.12***	-39.15	0.35	0.67
	(-1.65)	(0.90)	(2.49)	(-0.30)	(7.98)	(2.68)	(-1.33)	(0.81)	(1.64)
Regional dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Other controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adj.R-sq	0.350		0.532	0.253		0.317	0.262		0.404
Observations	568	568	568	211	186	186	357	348	348

Notes: robust t-statistics in parentheses; Male captures the sex of a child and the base category is ‘female’; Urban is a dummy for urban locality and the base group is ‘rural’; Regional dummies includes all the 10 regions of Ghana apart from ‘Upper West’, which is used as the reference category; Other controls included in the estimation are: (i) parental educational attainment, its base category being ‘no education’, and (ii) the square of the log of household income per capita (lnrealpc2); ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Source: authors’ construction.

Table 5: OLS, probit, and conditional OLS, full, and locality-disaggregated samples, 6–12 age cohort estimation

	Model 1 (Full sample)			Model 2 (Urban sample)			Model 3 (Rural sample)		
	Educexpend	**Anyexpend**	**Ln_Educexpend**	**Educexpend**	**Anyexpend**	**Ln_Educexpend**	**Educexpend**	**Anyexpend**	**Ln_Educexpend**
	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)
VARIABLES	Coef.	ME	Coef.	Coef.	ME	Coef.	Coef.	ME	Coef.
lnrealpc	-59.61***	0.50***	0.50***	-20.96	-0.71	0.95***	11.93	0.58***	0.51***
	(-2.77)	(3.56)	(4.39)	(-0.33)	(-1.21)	(4.64)	(1.30)	(3.65)	(3.65)
lnhsize	29.82***	0.08	0.08	55.53**	0.11	0.20***	15.05**	0.04	0.01
	(2.89)	(0.95)	(1.50)	(2.31)	(0.69)	(2.77)	(2.25)	(0.43)	(0.20)
Male	3.17	0.25***	0.06	-6.29	0.18	0.04	6.83	0.27***	0.08
	(0.34)	(3.03)	(1.15)	(-0.29)	(1.16)	(0.54)	(0.96)	(2.80)	(1.10)
Urban	102.33***	0.17*	0.73***						
	(10.22)	(1.76)	(13.26)						
Constant	-77.28***	0.35*	2.01***	-257.47***	5.43***	1.77***	-36.13***	0.35	2.18***
	(-3.34)	(1.74)	(14.60)	(-3.21)	(9.58)	(5.94)	(-2.69)	(1.49)	(12.61)
Regional dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Other controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adj.R-sq	0.364		0.472	0.340		0.422	0.192		0.316
Observations	2,287	2,249	2,249	918	888	888	1,369	1,361	1,361

Notes: robust t-statistics in parentheses; Male captures the sex of a child and the base category is 'female'; Urban is a dummy for urban locality and the base group is 'rural'; Regional dummies includes all the 10 regions of Ghana apart from 'Upper West', which is used as the reference category; Other controls included in the estimation are; (i) parental educational attainment, its base category being 'no education', and (ii) the square of the log of household income per capita (lnrealpc2); ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Source: authors' construction.

Table 6: OLS, probit, and conditional OLS, full, and locality-disaggregated samples, 13–15 age cohort estimation

	Model 1 (Full sample)			Model 2 (Urban sample)			Model 3 (Rural sample)		
	Educexpend	**Anyexpend**	**Ln_Educexpend**	**Educexpend**	**Anyexpend**	**Ln_Educexpend**	**Educexpend**	**Anyexpend**	**Ln_Educexpend**
	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)
VARIABLES	Coef.	ME	Coef.	Coef.	ME	Coef.	Coef.	ME	Coef.
lnrealpc	-2.05	0.41**	0.80***	185.69*	0.73	1.21***	21.67	0.38	0.44*
	(-0.06)	(2.13)	(4.39)	(1.77)	(1.50)	(2.85)	(1.15)	(1.55)	(1.92)
lnhsize	31.44**	0.00	0.06	55.74*	-0.00	0.18*	15.13	-0.00	-0.04
	(2.14)	(0.02)	(0.89)	(1.95)	(-0.03)	(1.91)	(1.20)	(-0.02)	(-0.40)
Male	0.13	0.18*	-0.02	12.73	0.39**	-0.01	-7.31	0.09	-0.01
	(0.01)	(1.77)	(-0.32)	(0.47)	(2.37)	(-0.10)	(-0.48)	(0.62)	(-0.12)
Head_male	-69.57		0.26				-37.50		-0.28
	(-1.55)		(1.46)				(-0.80)		(-0.91)
Urban	73.79***	0.12	0.62***						
	(4.44)	(1.01)	(8.25)						
Constant	-102.82***	0.83***	2.29***	-394.63***	0.95	2.15***	-29.51	0.86**	2.71***
	(-2.96)	(2.94)	(11.08)	(-3.38)	(1.30)	(4.25)	(-1.01)	(2.49)	(11.01)
Regional dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Other controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adj.R-sq	0.314		0.459	0.252		0.316	0.257		0.361
Observations	1,133	1,122	1,122	561	552	552	572	546	546

Notes: robust t-statistics in parentheses; Male captures the sex of a child and the base category is 'female'; Head_male captures the sex of a household head and the base category is 'female'; Urban is a dummy for urban locality and the base group is 'rural'; Regional dummies includes all the 10 regions of Ghana apart from 'Upper West', which is used as the reference category; Other controls included in the estimation are: (i) parental educational attainment, its base category being 'no education', and (ii) the square of the log of household income per capita (lnrealpc2); ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Source: authors' construction.

Table 7: OLS, probit, and conditional OLS, full, and locality-disaggregated samples, 16–18 age cohort estimation

	Model 1 (Full sample)			**Model 2 (Urban sample)**			**Model 3 (Rural sample)**		
	Educexpend	**Anyexpend**	**Ln_Educexpend**	**Educexpend**	**Anyexpend**	**Ln_Educexpend**	**Educexpend**	**Anyexpend**	**Ln_Educexpend**
	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)
VARIABLES	Coef.	ME	Coef.	Coef.	ME	Coef.	Coef.	ME	Coef.
lnrealpc	-94.31	-0.09	0.91***	-104.39	0.10	0.90***	67.08**	-0.07	0.97***
	(-0.84)	(-0.42)	(4.80)	(-0.29)	(0.22)	(2.60)	(2.01)	(-0.28)	(3.60)
lnhsize	18.76	0.07	0.09	21.89	0.02	0.02	26.33	0.12	0.24
	(0.62)	(0.82)	(1.01)	(0.34)	(0.18)	(0.17)	(1.35)	(1.02)	(1.56)
Male	-31.56	0.41***	0.07	-59.84	0.25*	0.05	51.53**	0.58***	0.21
	(-0.49)	(4.50)	(0.83)	(-0.50)	(1.84)	(0.44)	(2.13)	(4.58)	(1.48)
Head_male	-291.07*	-0.72**	-0.04	-464.00	-0.94**	-0.47	-37.76	-0.29	0.36
	(-1.89)	(-2.57)	(-0.13)	(-1.35)	(-2.26)	(-0.76)	(-0.52)	(-0.78)	(0.75)
Urban	129.03***	0.39***	0.48***						
	(3.45)	(4.05)	(4.82)						
Constant	-3.76	0.42*	2.84***	-87.40	1.22**	3.22***	-52.36	0.24	2.56***
	(-0.05)	(1.70)	(13.06)	(-0.32)	(2.06)	(7.22)	(-1.20)	(0.82)	(8.07)
Regional dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Other controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adj.R-sq	0.0364		0.429	0.0127		0.373	0.0832		0.263
Observations	1,024	1,024	1,024	491	485	485	533	533	533

Notes: robust t-statistics in parentheses; Male captures the sex of a child and the base category is 'female'; Head_male captures the sex of a household head and the base category is 'female'; Urban is a dummy for urban locality and the base group is 'rural'; Regional dummies includes all the 10 regions of Ghana, apart from 'Upper West' which is used as the reference category; Other controls included in the estimation are: (i) parental educational attainment, its base category being 'no education', and (ii) the square of the log of household income per capita (lnrealpc2); ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Source: authors' construction.

Table 8: OLS, probit, and conditional OLS, full, and locality-disaggregated samples, 19–24 age cohort estimation

	Model 1 (Full sample)			**Model 2 (Urban sample)**			**Model 3 (Rural sample)**		
	Educexpend	**Anyexpend**	**Ln_Educexpend**	**Educexpend**	**Anyexpend**	**Ln_Educexpend**	**Educexpend**	**Anyexpend**	**Ln_Educexpend**
	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)
VARIABLES	Coef.	ME	Coef.	Coef.	ME	Coef.	Coef.	ME	Coef.
lnrealpc	0.88***	-0.01	0.88***	-237.38	0.01	0.66*	17.43	-0.14	1.01**
	(3.72)	(-0.04)	(3.72)	(-1.40)	(0.05)	(1.76)	(0.63)	(-0.83)	(2.55)
lnhsize	0.24***	0.17***	0.24***	110.65***	0.27***	0.11	35.59*	0.03	0.46**
	(2.87)	(2.91)	(2.87)	(3.01)	(3.46)	(1.35)	(1.95)	(0.31)	(2.55)
Male	0.06	1.05***	0.06	213.06***	0.71***	0.08	233.82***	1.44***	0.03
	(0.58)	(14.50)	(0.58)	(3.78)	(7.10)	(0.72)	(6.00)	(13.50)	(0.16)
Head_male	0.07	-0.66***	0.07	-95.47	-0.26*	-0.03	-214.96***	-1.12***	0.29
	(0.41)	(-6.38)	(0.41)	(-1.19)	(-1.76)	(-0.20)	(-5.07)	(-7.33)	(0.76)
Urban	0.29***	0.35***	0.29***						
	(2.85)	(5.17)	(2.85)						
Constant	3.04***	-1.36***	3.04***	-32.46	-0.97**	3.95***	-92.43***	-1.25***	2.52***
	(11.24)	(-7.93)	(11.24)	(-0.19)	(-2.52)	(7.96)	(-2.77)	(-5.62)	(6.17)
Regional dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Other controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adj.R-sq	0.447		0.447	0.121		0.371	0.109		0.343
Observations	2,939	2,939	2,939	1,335	1,335	1,335	1,604	1,604	1,604

Notes: robust t-statistics in parentheses; Male captures the sex of a child and the base category is 'female'; Head_male captures the sex of a household head and the base category is 'female'; Urban is a dummy for urban locality and the base group is 'rural'; Regional dummies includes all the 10 regions of Ghana apart from 'Upper West', which is used as the reference category; Other controls included in the estimation are: (i) parental educational attainment, its base category being 'no education', and (ii) the square of the log of household income per capita (lnrealpc2); ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Source: authors' construction.

4.1 Discussion of results from conventional Engel curve estimations

In our baseline (2–24 years age cohort) estimation, the conventional Engel curve estimation suggests that factors such as household income, household size, parental educational attainment, gender of the household head, locality (urban dummy), and regional dummies significantly influence households' educational expenditure decisions. In particular, in Table 3 (column (a)), we find that household income is positively related to child schooling expenditure in rural Ghana, indicating that richer rural households tend to spend more on the education of their children than their less well-to-do counterparts. This finding is, however, less tenable in most of our age group-disaggregated estimations (Tables 4–8). For instance, for children in the basic education school-going age (2–15 years age cohort), household income does not influence child schooling expenditure in Ghana's rural areas. This incidence can be explained by the fact that in rural Ghana most basic education schools, which the majority of children attend, are free and hence differences in households' economic conditions may not be important.

We also find that household size is positively associated with child schooling expenditure. This suggests that larger households spend more on the schooling of a child than smaller households. Our finding on the effect of household size on child schooling expenditure in the baseline model is not corroborated by the results obtained from the 16–18 years age cohort estimation.

Female-headed households tend to spend more on schooling in Ghana than male-headed households; this is consistent with the results obtained from the locality-disaggregated sub-samples. For children in the post-senior high school-going age cohort (19–24 years), for instance, living in a female-headed household raises a child's educational expenditure allocation by over 200 cedis (US$36) relative to their counterparts from male-headed households in rural Ghana (see Table 8, column (a)).

Further, urban households spend significantly more on the education of their children than rural households; this may reflect differences in the cost of schooling a child across localities as well as locality-based differences in parental awareness about the benefits of education. Parental educational experience exerts an increasing positive influence on children's educational expenditure allocations, indicating perhaps that better-educated parents are more conscious about the perceived benefits of education and so are relatively more willing to spend more on the schooling of their children. These results are broadly consistent with the outcomes from the age group-disaggregated sub-sample estimations (column (a) of Tables 4–8). Regional dummies indicate higher educational expenditure allocations in the southern regions of Ghana than in the Upper West region; this result is broadly consistent with estimates from the hurdle models.

We now turn our attention to the issue of most interest in this paper: whether there are gender-differentiated treatments in households' educational expenditure allocations. A summary of the results of the effect of gender in our educational expenditure allocation models is presented in Table 9. The gender coefficients for the unconditional OLS (conventional Engel curve) estimates are presented in column (c) of Table 9. The empirical results therefrom suggest the presence of a significant pro-male bias in intra-household educational expenditure allocations for children in the effective school-going age in Ghana (2–24 years age cohort) (see Panel A of Table 9, column (c)). Specifically, we find that, relative to girls, boys receive over 53 cedis (US$9.50) per annum more in educational expenditure allocations in Ghana; this is corroborated by the results in the rural sub-sample estimation but not in the urban sub-sample estimation. Thus, it can be argued that the pro-male bias we observe in the full sample estimation is driven only by the strong presence of a pro-male bias in Ghana's rural areas. However, by disaggregating the effective school-going age sample into five distinct categories in line with Ghana's educational system as indicated earlier, we observe important differences in the role of a child's gender in determining the flow of household resources to finance his/her education.

Table 9: Coefficient of gender variable (Male): age cohorts and locality-disaggregated estimates

	Probit of positive Educexpend	**Conditional OLS of Educexpend**	**Unconditional OLS (conventional Engel curve)**
Sample	(a)	(b)	(c)
Panel A: full sample (2–24 years)			
Ghana	0.61 (18.00)	0.13 (3.62)	53.21 (3.33)
Urban	0.46 (8.95)	0.07 (1.45)	43.56 (1.20)
Rural	0.72 (15.92)	0.19 (3.69)	62.28 (6.84)
Panel B: pre-primary sub-sample (2–5 years)			
Ghana	-0.12 (-0.91)	0.14 (1.27)	9.43 (0.49)
Urban	0.01 (0.03)	-0.03 (-0.19)	15.09 (0.35)
Rural	-0.19 (-1.22)	0.30 (1.95)	10.72 (0.86)
Panel C: primary sub-sample (6–12 years)			
Ghana	0.25 (3.03)	0.06 (1.15)	3.17 (0.34)
Urban	0.18 (1.16)	0.04 (0.54)	-6.29 (-0.29)
Rural	0.27 (2.80)	0.08 (1.10)	6.83 (0.96)
Panel D: junior high sub-sample (13–15 years)			
Ghana	0.18 (1.77)	-0.02 (-0.32)	0.13 (0.01)
Urban	0.39 (2.37)	-0.01 (-0.10)	12.73 (0.47)
Rural	0.09 (0.62)	-0.01 (-0.12)	-7.31 (-0.48)
Panel E: senior high sub-sample (16–18 years)			
Ghana	0.41 (4.50)	0.07 (0.83)	-31.56 (-0.49)
Urban	0.25 (1.84)	0.05 (0.44)	-59.84 (-0.50)
Rural	0.58 (4.58)	0.21 (1.48)	51.53 (2.13)
Panel F: post-senior high sub-sample (19–24 years)			
Ghana	1.05 (14.50)	0.06 (0.58)	0.06 (0.58)
Urban	0.71 (7.10)	0.08 (0.72)	213.06 (3.78)
Rural	1.44 (13.50)	0.03 (0.16)	233.82 (6.00)

Notes: robust t-statistics are in parenthesis and the shaded cells indicate significance at the 1% level or more; the base category for the gender variable (Male) is female.

Source: authors' construction.

The conventional Engel curve estimations for children in the basic, pre-primary, and primary education school-going age cohorts (i.e. 2–5 years, 6-12 years, and 13-15 years sub-sample estimations) strongly suggest the absence of gender-differentiated treatment in households' educational expenditure allocations (see Table 9, column (c), Panels B, C, and D); the case is, however, not the same for children in the senior high school and post-secondary schooling age cohorts. That is, for children in the basic education age cohorts, households do not discriminate according to the gender of the child in their allocation of resources for child schooling, conditional on enrolment in school, while some evidence of gender discrimination is present among children in the post-basic education schooling age cohort. For children in the senior high school-going age cohort, an important pro-male bias is observed in rural Ghana, while no gender discrimination exists in households' educational expenditure allocation in urban areas. Further, among children in the post-senior high school-going age cohort, households significantly discriminate against girls in their educational expenditure allocation in both rural and urban areas (see Panel F, column (c) of Table 9).

In sum, the conventional Engel curve model established the presence of gender bias *only* in the full sample (2–24 years) and somewhat in the post-basic education schooling age cohort. However, the capacity of the Engel curve approach to detect gender bias in households' schooling expenditure allocation for children in these age groups can be attributed to the non-complexity of the gender effects in such cases.

4.2 Discussion of results from the hurdle model estimations

As stated earlier, columns (b) and (c) of Tables 3–8 report the hurdle model estimates. Column (b) presents estimates from the first 'hurdle'—the probability that the household spends anything on a child's education (Anyexpend), i.e. it has a positive educational expenditure. Column (c) reports estimates of the second stage—the natural logarithm of educational expenditure (Ln_Educexpend) conditional on choosing a positive educational expenditure. Like the conventional Engel curve estimates, the empirical results from the hurdle model estimates broadly suggest the importance of factors such as household income, household size, parental education, gender of a child, gender of the household head, and contextual factors (such as locality) in influencing both the positive expenditure and the conditional expenditure decisions.

In particular, the first-stage results (i.e. probit of Anyexpend) show that household income is positively related to the probability of a child having a positive educational expenditure allocation in the full sample (2–24 age cohort) in Ghana (see Table 3, column (b)); however, this incidence is present only in rural Ghana for the full sample estimation. The implication of this is that, in rural Ghana, relative to children from less economically well-off households, children from richer households are more likely to have a positive educational expenditure allocation (i.e. to be enrolled in school). However, this is not the case for children living in urban areas. In urban areas, child school enrolment probabilities may not differ much across households with different economic conditions because most urban households are aware of the benefits of sending a child to school and so most will want to send their children to school irrespective of their economic conditions. This finding lines up, largely, with the age group-disaggregated estimations.

In addition, household size raises the probability of child school enrolment in the full sample; this is true for the locality-disaggregated sub-sample estimations. This may imply that larger households are associated with the presence of more working adults, who tend to provide support for younger household members to access school.

Consistent with the findings of earlier studies (see, for example, Iddrisu et al. 2016, 2017), we observe that female headship is a significant positive predictor of child school enrolment in Ghana; this is corroborated in our locality-disaggregated sub-sample estimations and also in the age group-disaggregated models (Tables 4–8).

Urban households are significantly more likely to spend a positive amount on child schooling relative to their rural counterparts.

As in the conventional Engel curve estimation results, parental education is positively related to the probability of enrolling a child in school.

Regarding the second-stage estimations of the hurdle model (i.e. the conditional expenditure model), we find that household income relates positively to child schooling expenditure, indicating that richer households spend more on their children's education than less well-to-do households; this is true in the locality-disaggregated models as well. The signs of the coefficients of household size, and locality (urban versus rural) in the second-stage estimations are consistent with what is observed in the first-stage estimation. This, implies, for instance, that urban locality is a positive predictor of both school enrolment and how much is spent on the schooling of a child conditional on enrolment.

Contrary to the results obtained in the first-stage estimations, we observe that female headship is a significant negative predictor of conditional educational expenditure; this is true for the locality-disaggregated sub-sample estimations as well. This means that after *all* children are enrolled in school, children who live in households that are headed by males receive a higher educational expenditure allocation than their counterparts who live in female-headed households. This may reflect differences in the economic conditions of male- versus female-headed households.

We now address the primary objective of this paper: detecting gender bias in children's educational expenditure allocation with a hurdle model framework. As noted earlier, the coefficients of the gender variable in all our estimations are summarized in Table 9. Columns (a) and (b) present the coefficients of the gender variable from the first 'hurdle'—i.e. the probit of positive educational expenditure—and the second 'hurdle'—i.e. the conditional OLS of educational expenditure—respectively. More interesting findings emerge from the hurdle model estimates than from the Engel curve results. In column (a) of Table 9, we observe the presence of a significant pro-male bias in the positive educational expenditure decision in Ghana for the full sample (all children in the effective schooling age cohort); this is consistent with evidence from the locality-disaggregated sub-sample estimations. The implication of this result is that boys are more likely to be enrolled in school than girls.

However, when we disaggregate this sample into the Ghanaian educational system's age groupings, we observe that a pro-male bias in child school enrolment does not exist among children in the pre-primary school-going age cohort (2–5 years), nor for children in the primary schooling age cohort (6–12 years) in urban Ghana or children in the junior high school-going age cohort (13–15 years) in rural Ghana. The absence of a pro-male bias in households' decision to enrol children in the primary schooling age cohort in school in urban areas can be explained by the fact that urban households have become more aware of the importance of educating a child—especially girls—through the media coverage that followed the 'Girl Child' education campaign launched in the early 2000s. Further, the absence of a pro-male bias among children in the junior high school-going age cohort in rural Ghana can be attributed to the fact that in rural Ghana both boys and girls at that age are similarly disadvantaged in terms of access to education, due perhaps to the absence of secondary schools in rural areas.

An important pro-male bias is, however, present in households' decision whether to enrol children in the primary school-going age cohort in school in rural Ghana. That is, in rural areas, boys are significantly more likely to be enrolled in school than girls. For children in the junior high school-going age cohort in urban Ghana, there is a significant pro-male bias in households' school enrolment decisions. This result is puzzling. One may, however, interpret it as reflecting the fact that children in the 13–15 age bracket—especially girls—are more likely to be engaged as child workers to help with family income in urban areas.

For children in the post-basic education cohort (16–24 years), a strong pro-male bias exists in the probability of a positive education expenditure decision of households in Ghana; this is supported by the locality-disaggregated estimates. That is, for children in the senior high schooling age cohort or higher, households are more likely to enrol a boy in school than a girl. This finding may reflect the fact that, unlike boys, most girls drop out of school after completing basic education due to a number of social factors that affect girls but not boys, such as pregnancy.

In column (b) of Table 9, we find the presence of gender bias in households' conditional educational expenditure decision for children in the 2–24 years age cohort in Ghana. This is driven by the presence of gender-differential treatments in households' decision how much to spend on the education of a child after that child is enrolled in school in rural Ghana. The existence of a pro-male bias in households' conditional educational expenditure decision reinforces the pro-male bias that is present in the binary decision of a positive educational expenditure, thus yielding a strong pro-male bias in households' education expenditures, as observed in the Engel curve estimation.

The results from the conditional child schooling expenditure decision in the age group-disaggregated estimations do not support the presence of a pro-male bias phenomenon in households' conditional educational expenditure decisions. In particular, we observe that, after enrolling boys and girls in the primary and beyond primary age cohorts, households do not allocate a dissimilar amount of resources towards the schooling of boys and girls; this is in contrast to the findings of Aslam and Kingdon (2008), who observed a pro-male bias in households' conditional education spending for children in the 10–14 and 15–19 age groups. Thus, our hurdle model estimates suggest, broadly, that the presence of gender bias in households' educational preferences is seen in the binary decision of whether to enrol boys and girls in school but not in the conditional decision of how much to spend on enrolled boys and girls (Iddrisu et al. 2018); clearly, by averaging the (often) oppositely signed probit and conditional expenditure gender effects—as is implicit in the Engel curve approach—one is more likely to conclude that there is an absence of gender bias, and would miss the fact that there is bias through one of the channels (i.e. the positive educational expenditure decision).

In sum, comparing the hurdle model outcomes with the conventional Engel curve method results, we show that, by 'unpacking' the two potential sources of gender bias, the hurdle model makes the detection of gender bias much easier relative to the conventional Engel curve method (Iddrisu et al. 2018). The results in Panels C and D of Table 9, for instance, show this clearly. In Panel C, the conventional Engel curve method failed to detect gender bias in households' education expenditure allocation, while the hurdle model demonstrated the presence of gender-differentiated treatment in households' educational expenditure allocations, the bias arising from the decision whether to enrol boys and girls alike in school. The inability of the Engel curve method to detect bias in this case can be explained by the fact that the bias operated through only one of the channels (i.e. the positive educational expenditure decision), even though the coefficients of the gender variable in the two channels had the same sign. In Panel C, however, the bias again occurred in only the positive educational expenditure decision, the coefficients of the gender variable in the two channels being oppositely signed. By averaging these two coefficients, the Engel curve approach is less likely to detect gender bias. Thus, by disaggregating the household educational expenditure decision into the two distinct but dependent parts, our hurdle model allows us to observe the presence of a gender bias in households' educational expenditure allocations, at least, through one of the two channels.

5 Conclusion

This study explored the presence (or otherwise) of a gender-differentiated treatment in households' educational expenditure allocations using individual-level expenditure data from the latest wave of the Ghana Living Standards Survey (GLSS 6) data set. The study utilized a hurdle model to 'unpack' the sources of gender bias in households' education expenditure allocations. We also compared the outcomes of the hurdle models with those from a conventional Engel curve estimation in order to provide some evidence of the relative superiority of the hurdle model in fitting models with a corner solution outcome. Our empirical results reveal a number of interesting findings.

First, the study showed the importance of both household income and household size in explaining educational expenditure allocations; household income crucially drives both the probability of enrolling a child in school, especially in rural areas, and the amount spent on schooling a child upon enrolling her in school.

Second, urban locality is a positive predictor of both school enrolment and relatively high spending on the schooling of a child conditional on her being enrolled in school.

Third, female headship is a significant positive predictor of households' decision to enrol boys and/or girls in schools in both urban and rural areas. However, conditional upon enrolling boys and/or girls in school, male-headed households commit more resources towards the schooling of children than female-headed households. This means that after *all* children are enrolled in school, children who live in households that are headed by males receives a higher educational expenditure allocation than their counterparts who live in female-headed households. This may reflect differences in the economic conditions of male- versus female-headed households.

Fourth, educated parents are more highly committed towards the schooling of their children than uneducated parents.

Fifth, gender bias in households' educational expenditure allocations arises mainly from households' decision to enrol boys and girls in school. For children in the basic education school-going age cohort and beyond, an important pro-male bias exists in households' decision to enrol boys and girls in school but not in the conditional educational expenditure decision. That is, households discriminate across gender in their decision to enrol a child in school in Ghana. However, after enrolling both boys and girls in school, households tend to spend an equal amount on the schooling of boys and girls. These findings have important implications for educational policy design, especially in the context of developing countries.

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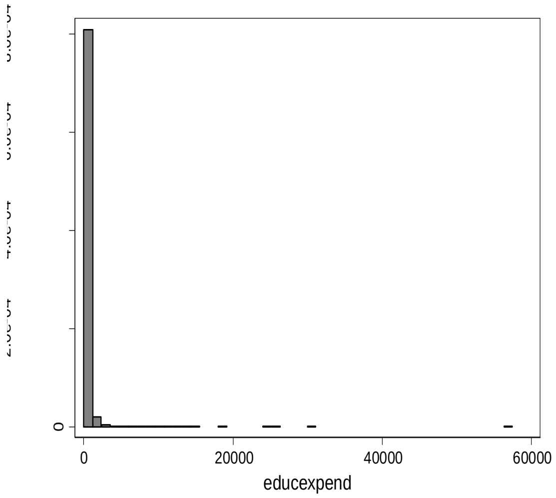
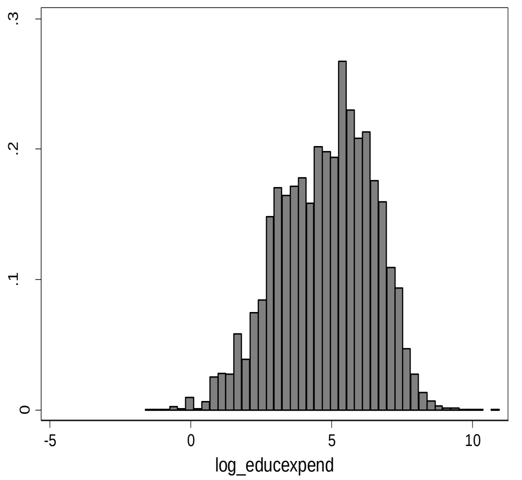
Appendix: Distribution of conditional expenditure

Figure A1: Graph of Educexpend (right-skewed distribution)



Source: authors' construction.

Figure A2: Graph of log(Educexpend) (more normal distribution)



Source: authors' construction.