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Examining Child Labor and Parental Altruism from the Rural-Urban Divide: Extending the Inverted-U Empirics

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Abstract
Extending the current empirical discourse on the inverted-U to cover non-farm households, this paper replaces the land size (proxy for wealth) with a fully-composed household income from the GLSS6 data that incorporates the value of land and five other components as income. After choosing the ZIP model over the PRM, based on the corrected versions of the Vuong test, the findings supported the inverted-U relationship between household income and child labour. This implies that, at lower levels of income, parents are non-altruistic, using more child labourers with increases in income but become altruistic towards their children at income levels beyond GH₵11,656.2760 ($5,834.26) for all households; GH₵11,308.3877 ($5,660.14) and GH₵22,026.4658 ($11,024.81) for the rural and urban households respectively. The analysis showed that rural-located parents become altruistic at relatively lower levels of income compared to their urban counterparts. Policy should aim at increasing the average income of households.

JEL Classification: *D10, I21, J21, J23, J43, Q12*
Keywords: wealth paradox, child labour, altruism, rural, urban

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Introduction

Child labourers, in Ghana, contribute significantly to household incomes, both from farm and non-farm economic activities (Koomson and Asongu, 2016). Cockburn (2002) has also indicated that child labourers in Ethiopia, on the average, contribute 4 to 7 percent of household income while some of the children even contribute up to 50 per cent. From the evidence above, one may likely expect that parents and guardians will have an insatiable need for child labourers due to the income-generating benefits they derive from them. This notwithstanding, there is a huge double-edged body of the extant literature that point to the fact that household income can either perpetuate child labour (non-altruistic theory) or reduce it (altruistic theory).

A myriad of studies have indicated that parents are indeed altruistic but send their children to work, rather than school, because of poverty (Bhaskar and Gupta, 2012). This then implies that, increasing the income levels of such parents will result in decreasing number of child labourers at the household level. Again, the seminal work by Basu and Van (1998) indicated that child labour decreases with increases in household resources and also based on the "luxury axiom[1]". In what has come to be termed the wealth paradox, other studies have also argued that parents are non-altruistic (selfish) and exploit their children even in the presence of high income levels which could also emanate from problems that the poor have with elements of self-control (Banerjee and Mullainathan, 2010; Lima et al., 2015). Bhalotra and Heady's (2003) study in rural Pakistan pointed out that land-rich parents caused their children to work more than land-poor parents just as Bandara et al (2015) observed increasing child labour hours for income shocks at the household level in Tanzania. Rogers and Swinnerton (2004) also have posited that if the degree of parental altruism is sufficiently low, child labour could persist even in the presence of high parental income and similar findings can be found in the works done in developing countries by Dumas (2007) and Kruger (2007).

Another side to the afore mentioned findings is the study by Basu et al. (2006) that deviate from the earlier studies, showing a linear relationship between child labour and household wealth (or income), to embrace a curve-linear relationship (inverted-U) between household wealth and child labour. Specifically, they showed that increasing the size of agricultural land up to about 4 acres results in a decline in child labour phenomenon in the household. Lima et al. (2015) also found the Inverted-U evidence and looked at the gender perspective for Pakistan. Kambahampati and Rajan (2006) looked at child labour and economic growth in India and found an inverted-U (child labour-Kuznets curve) and considered the gender perspective. Most of these studies mainly focus on agriculture households that have their wealth stored in the form of land which suggests that urban households are largely left out of these studies, making the rural-urban empirics, in general, missing in the extant literature. Since child labourers contribute to both farm and non-farm incomes (Koomson and Asongu, 2016), and the non-farm households in Ghana were proportionately 63.6 percent urban-located[2] and 36.4 percent rural in 2012/2013 (Ghana Statistical service – GSS, 2014), focusing on agriculture households has an implicit problem of sample selection bias. Siddiqi and Patrinos (2002) have pointed at rural-urban migration as a cause of child labour in urban areas of developing countries. The world Bank also notes that urban poverty in sub-Saharan Africa (SSA), and in many countries, is a sign of urban poverty (Baker, 2008). It is on the back of this urban dimension to the child labour parental relations, in addition to the rural component, that this study seeks to rope in the urban households to

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[1] Children are sent to the labour market only if family's no-child labour income drops very low

[2] Because non-farm economic activates are mainly undertaking by urban households, I partly use non-farm and urban households interchangeably. This is not to say that non-farm economic activities are undertaking only by urban households but they generally represent what it stands for in this paper.

determine the relative levels of altruism between rural and urban households after it has established the possible existence or inexistence of an inverted-U relationship if the current literary discourse is extended to cover non-farm households.

In the Ghanaian and SSA context, a number of studies have been done on child labourers and their educational outcomes (Boozer and Suri, 2001; Hashim, 2007); in cocoa and other farming activities (Abenyega and Gockowski, 2003; Owusu and Kwarteye, 2008; Basu et al., 2010); artisanal mining (Hilson, 2010); in fisheries and aquaculture (Afenyadu, 2010) among others, which passively explain some aspects of parental altruism/non-altruism, but a study that places emphasis on parental altruism is missing and the rural-urban empirics can also not be said for Ghana, although child labour is a big development issue in Ghana. We are, at the moment, in doubt if Ghanaian parents are altruistic or non-altruistic in their child labour relations. If they are, at what levels of income are they altruistic and how does this altruism play out in rural and urban areas of the country.

This geographical (locational) dimension is paramount because child labour in many parts of SSA has been noted as being more of a rural phenomenon than an urban one. That notwithstanding, urban poverty and rural-urban migration have also been documented as playing a role in explaining child labour so adding the urban dimension to the discourse on child labour and parental altruism cannot be overemphasized. The urban component will help to determine whether urban parents are more altruistic than their rural counterparts by establishing the income level at which parents can be seen as altruistic or not. Bringing on board the urban dimension of the discourse resolves the potential sample-selection bias that might produce biased estimates when excluded from the study. It is in the light of this that this study extends the study to cover non-farm households which, by a larger implication, ropes in the urban component into the discussion. The rest of the paper is structured in the following order: next comes the analytical framework and rationale for replacing the income variable. This is followed by data source and data processing, test of altruism and estimation techniques. Section four presents the results and discussion while the final section concludes and provides recommendations.

Analytical Framework

This paper adapts the Basu et. al. (2010) framework which was built on the two-period model by Bhalotra and Heady (2003). Although these models focus on farm households, the current paper extends the unit of analysis to cover both farm and non-farm households and also replaces the household wealth, which is proxied with land size, in Basu et. al.'s model with household income (see rationale for this replacement explained after the theoretical model). The model assumes that each household has the utility;

$$u = u(x, e) \tag{1}$$

where, x is the household's total consumption and $e \ \varepsilon [0,1]$ is the amount of work done by child labourers in the household. It is assumed that each household has one adult (could be the household head) who finds it worthwhile to work because this adult considers his/her leisure to be of no worth. The model emphasizes the polar case of labour market imperfection (no buying or selling of labour) and this happens because: (1) workers find it tedious to work for others and choose not to do so (2) employers only rely on domestic labour because they attach a high moral hazard to outside labour. Based on the above, the production function facing each household is given as

$$q = f(k, e+1) \tag{2}$$

where, q is output produced, k is the size of land used and $e+1$ is the amount of labour used — e from child labour and 1 from the adult. Basu et al. proved theoretically and empirically that in an imperfect labour market situation, increases in household wealth (k) can lead to a rise or a fall in (e). Their study supported the fall in child labour largely due to the luxury axiom and so did studies like that of Bhalotra and Heady (2003) and Bhaskar and Gupter (2012).

Rationale for replacing the land with a fully composed household income

I replace land with the fully composed household income because: (1) Balhotra and Heady (2003), like other researchers, that use land, mainly concentrate on farm households but this study includes child labourers in non-farm households so using the size of agricultural land will result in zero agricultural land for all non-farm households included in the study. (2) The income in the GLSS6 data encompasses income from six different sources — ***income from employment, household agriculture, non-farm self-employment, rent and other sources (such as pension receipts, interests on savings and investments and others).*** It should also be noted that this income represents wealth more than just land because agriculture income is computed by estimating the cost of all inputs which includes land, seed, fertilizer, feed and others. In fact, studies by Rogers and Swinnerton (2004) and de Carvalho Filho (2012) have all tested for parental altruism using household income. With the reason for replacements made clear, I now adjust and present the generally estimable equation as drawn from the literature and used in Basu et al. (2010) below:

$$y_h = \alpha_v + X_i\beta_i + X_h\beta_h + e \qquad (3)$$

where the dependent variable y_h is the number of child labourers in each household, X_i is a vector of child-specific characteristics (age of child labourer, gender and educational status of children) while X_h is a vector of household characteristic (household income, gender of household head, location of the household, number of older household members and many others).

Data Source and Data Processing

The data for this study is the sixth round of the Ghana Living Standards Survey (GLSS6) and was collected by the GSS (2014). It is nationally representative and cut across all the ten administrative regions of Ghana. The survey which covered a sample of 18,000 households in 1,200 enumeration areas was collected over a one year period from 18th October 2012 to 17th October 2013. At the end of the survey, 16,772 out 18,000 enumerated households, were successfully covered, leading to a response rate of 93.2 percent. After merging files from various sections of the data, the number of households reduced to 19, 252. Finding the natural log of the household income resulted in further reduction to 19,162 households. The final loss of observations was at the regression stage, where missing observations in some rows and columns reduced it further to 19,147 and this formed the final sample size that was used for the study. The survey used a multi-stage sampling approach and unlike previous rounds, the GLSS6 introduced a Labour Force Survey module with additional sections on Child Labour. The child labour variable is defined in conformity with ILO Convention 138 (and adopted by the GSS) which is children who are a below 15 years but are economically engaged.

Table 1 shows that child labour is largely a rural phenomenon since majority (57%) of child labourers reside in the rural areas. Supporting this assertion is also the situation where, for households that had no child labourer in the house, the urban households were more (53%) than their rural counterparts. For households having at least one child labourer (1 to 7), the rural households consistently outnumbered their urban counterparts. This gives credence to the separate estimations for rural and urban households beside the full model so as to factor in the rural-urban heterogeneity in parent and child labour relations.

Table 1: Number of Child Labourers in household by Location (Within and across frequencies)

Number of Child Labourers in a household	Within-Group Frequencies (Row Percentages)			Across Group Frequencies (Column Percentage)
	Location			
	Urban (%)	Rural (%)	Total (%)	
0	6,381 (53)	5,645 (47)	12,026 (100)	62.8
1	629 (26)	1,765 (74)	2,394 (100)	12.5
2	766 (33)	1,535 (67)	2,301 (100)	12
3	177 (14)	1,051 (86)	1,228 (100)	6.4
4	117 (23)	386 (77)	503 (100)	2.6
5	120 (33)	240 (67)	360 (100)	1.9
6	18 (10)	162.(90)	180 (100)	1
7	26 (17)	127 (83)	153 (100)	0.8
Total	8,235 (43)	10,912 (57)	19,147 (100)	100

Source: Author's computation using GLSS6 data

The column percentage (Table 1) shown in the last column indicates that there is a huge number of households reporting zero for existence of child labourer and this is, in practice, made up of those that are classified as "certain zeros" (generating data through a binary process) and actual zeros (generating data through a count process). It is due to the clustering of about 63 percent of households at the zero category that we use both the Poisson Regression Model (PRM) and the Zero-Inflated Poisson (ZIP). The PRM and ZIP models and the choice between them, based on the Vuong Test, are thoroughly dealt with at the estimation technique section.

Summary Statistics

The Distribution of child labourers across households (Table 2) in the study shows that every household has at least one child labourer, with the rural households having more on the average than urban-located households. The average income for these households is GhȻ17,634.62 ($8,826.58)[3] and this is specifically, GhȻ13,189.970 ($6,601.92) and GhȻ26,162.800 ($13,095.15) for rural and urban households respectively. Looking at the age of child labourers shows that it conforms to the standard definition for child labour (below 15 years) and the minimum age of five is the starting age for respondents in the dataset used.

[3] Exchange rate is US$1= GH¢1.9979 — the exchange at the end of the data collection on 17th October 2013 and can be traced from the Bank of Ghana website on https://www.bog.gov.gh/markets/daily-interbank-fx-rates

Table 2: Summary statistics of variables used in the study and in estimating the effect of household income on Child labour

	Full Model		Rural Model		urban Model	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Number of Child Labourers	0.795	1.313	1.021	1.427	0.362	0.918
Household income	17634.62	52803.70	13,189.970	33706.760	26162.800	76473.360
Age of child labourer	9.415	2.848	9.354	2.834	9.532	2.871
Female child	0.488	0.500	0.478	0.500	0.508	0.500
School-going child (1=schooling; 0=not schooling)	0.917	0.276	0.886	0.317	0.975	0.156
Rural (1= rural; 0= urban)	0.657	0.475	—	—	—	—
Age of household head	47.619	13.200	48.200	13.580	46.505	12.365
Poor (1=poor; 0= not poor)	0.398	0.489	0.522	0.500	0.161	0.367
Male household head (1=male; 0=female)	0.773	0.419	0.817	0.387	0.689	0.463
Educational level of household head (Base=No education)						
Basic School	0.257	0.437	0.287	0.452	0.201	0.401
Secondary School	0.317	0.465	0.245	0.430	0.455	0.498
Post-secondary and Tertiary	0.065	0.247	0.032	0.177	0.129	0.335
Number of older household members	6.155	3.000	6.390	3.248	5.705	2.391
Region (Base=Western)						
Central	0.084	0.277	0.079	0.270	0.093	0.290
Greater Accra	0.075	0.263	0.016	0.127	0.187	0.390
Volta	0.091	0.288	0.100	0.300	0.075	0.263
Eastern	0.097	0.296	0.090	0.287	0.109	0.312
Ashanti	0.101	0.302	0.075	0.263	0.152	0.359
Brong Ahafo	0.100	0.301	0.097	0.295	0.108	0.311
Northern	0.141	0.348	0.168	0.374	0.090	0.286
Upper East	0.096	0.295	0.120	0.325	0.051	0.219
Upper West	0.120	0.325	0.164	0.370	0.035	0.184
Economically employed child < 15 years (1=yes; 0=no)	0.258	0.438	0.326	0.469	0.129	0.335
Number of Obs. (N)	**19,147**		**12,587**		**6,560**	

Source: Author’s computation using GLSS6 data

A Test of Altruism

I test for altruism by using non-parametric regression to explore the bivariate relationship between income and the number of child labourers in the household. To cater for possible biases resulting from heterogeneity and outliers in households' income, I derived the natural log of the income variable to smoothen it before doing the bivariate analysis. After obtaining the stationary points for incomes at which parents were considered altruistic, I derived the actual income by finding the exponents of these stationary points. For all three, the Inverted-U evidence for the relationship between child labour and household income was found, giving stationary points of GH₵11,656.2760 ($5,834.26) for the full sample; GH₵11,308.3877 ($5,660.14) and GH₵22,026.4658 ($11,024.81) for the rural and urban sub-samples respectively. This implies that parents are non-altruistic at lower levels of income but become altruistic at relatively higher levels of income. Comparing the stationary points for rural and urban parents, conclusions can be drawn to the fact that parents in rural areas become altruistic towards child labourers at lower levels of income than parents residing in urban locations. This might be justified by the relative cost of living in these areas since the cost of living in the urban areas is much more than what is needed to earn a decent living in the rural area.

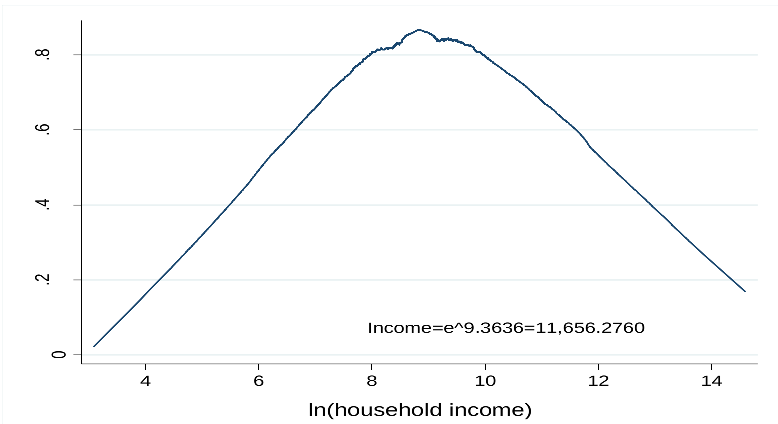

Fig. 1. Child labour and household income (Ghana)
Source: Author's computation using GLSS6 data

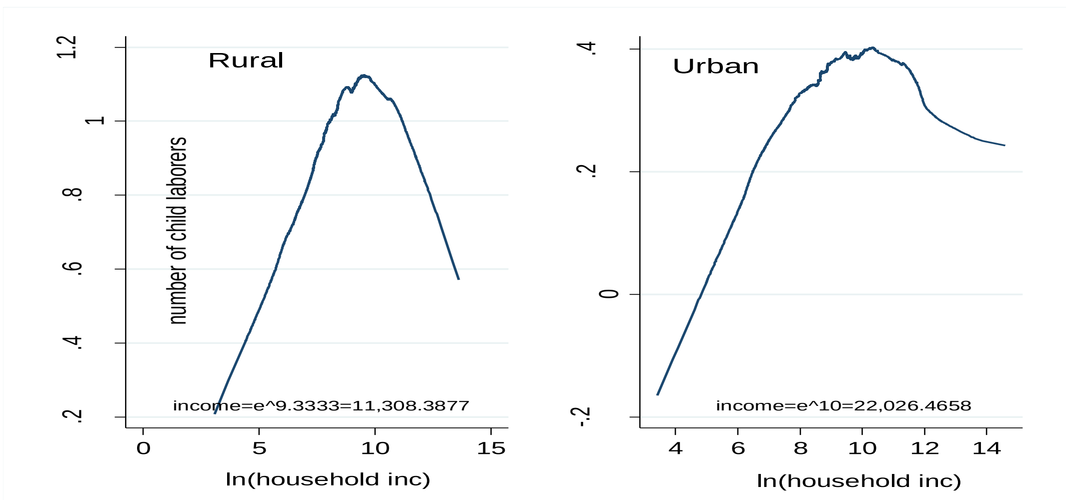

Fig. 2. Child labour and household income (rural and urban areas)
Source: Author's computation using GLSS6 data

Regression for Household Income and Child labour
Estimation Techniques

Since the dependent variable is the number of child labourers in each household, I resort to the use of count data models. Due to the possibility of over dispersion of excess zero in the child labour variable resulting in biased estimates (see Table 1), I determine which technique best-fits the data by estimating the PRM and ZIP and go ahead to decide using the Vuong test. A significant Vuong test means that the ZIP model, which accounts for two data generating processes, fits the data better by correcting for the over-dispersion of zeros and giving reliable estimates (Vuong, 1989; Greene, 1994).

The Poisson Regression and Zero-Inflated Poisson Models

According to Gujarati (2004), a Poisson regression will treat the number of child labourers as a Poisson random variable with an intensity hypothesized to depend on posited explanatory variables. The key assumption that underlies the Poisson Regression Model is the equality in the expected value and the variance of the error terms. A random variable X is Poisson distributed if its probability distribution function is given by

$$\rho(Y = y) = f(x) = \frac{\mu^{y} \ell^{-\mu}}{Y!} \tag{4}$$

Where $Y = 0,1,2,3,.....$ denotes the count process *and* $\mu > 0$

we assume $\pi_i = \pi(v, \theta)$. Where $v =$ a vector of explanatory variables and $\theta =$ number of child labourers. If the number of child labourers for each household is known, CL_i, then according to the Poisson specification, we have:

$$\rho(CL_i) = \frac{\mu^{LR_i} \exp^{(-u_i)}}{CL_i!} \tag{5}$$

In a sample where we have households with child labourers $\{CL_i, ..., CL_n\}$, the corresponding log-likelihood function is the logarithm of the product of the marginal probabilities.

In reality, a count variable may contain excess zeros, causing a higher probability of zero values than is consistent with the PRM (see Table 1). In this case, it could be assumed that zeros and positive values do not come from the same data generating process (Winkelmann, 2013) and using a PRM on such data will result in biased estimates. To cater for excess zeros, the zero-inflated Poisson model can be used to accommodate both data generating processes.

The zero-inflated Poisson model allows for two different data generating regimes: the outcome of regime 1 (R1) is always zero, whereas the outcome of regime 2 (R2) is generated by a Poisson process (Lambert, 1992; Greene, 1994; Bauer and Sinning, 2010; Cameron and Trivedi, 2010). In this model, the "unconditional" expectation of the dependent variable consists of the conditional probability of observing regime 2 and the conditional expectation of the zero-truncated density which is presented in equation 6.

$$\begin{cases} \Pr(LR_i = 0 \mid X_i) = \Pr(R1) + \Pr(LR_i = 0 \mid X_i, R2)\Pr(R2) \\ \Pr(\mathrm{LR_i} = \mathrm{j}|\mathrm{X_i}) = \Pr(\mathrm{LR_i} = \mathrm{j}|\mathrm{X_i}, R2)\Pr(R2), \quad \mathrm{j} = 1,\ 2,\ 3,.... \end{cases} \tag{6}$$

Lambert (1992) specifies the conditional probability of regime 1, that always leads to a zero outcome, as a Logit model:

$$pr\left(R1/X_i\right)=\frac{\exp\left(\gamma Z_i\right)}{1+\exp\left(\gamma Zi\right)} \tag{7}$$

Where, Z_i contains the covariates of the conditional probability of excess zeros and γ is the parameter vector to be estimated. Consequently, the unconditional mean of the dependent variable is specified in equation (8) as;

$$S\left(\hat{\beta}_i^{ZIP}, X_i\right)=\frac{1}{N_g}\sum_{i=1}^{N}\left[1-\left(\hat{\Pr}\left(R1\right)|X_i\right)\right]\hat{\mu}_i=\frac{1}{N}\sum_{i=1}^{N}\frac{\exp\left(\hat{\beta}_i^{ZIP}, X_i\right)}{1+\exp\left(\gamma Zi\right)} \tag{8}$$

Stated simply, R1 is generated through a binary process and takes account of households that have child labourers and those who have children less than 15 years but are not economically employed. R2 is also generated through a Poisson (count) process and takes account of both genuine and certain zeros in addition to counts beyond zero. The genuine zero is where the household has children less than 15 years but has no child labourer and the certain zero is the household that may either have no child in the house or has children but are more than 15 years and for this reason, will certainly report zero for the number of child labourers regardless of the condition. The certain zero condition is what might possibly account for about 63 percent of households (Table 1) reporting zero for the number of child labourers. The variable/question that generates this logit process is whether a household has a child who is less than 15 years old and is economically employed or not and is used as the source of inflation to model the zero-inflated Poisson. I run the PRM and ZIP models and apply the corrected versions of the Vuong test to determine which model best fits the data.

Vuong Test for choosing between PRM and ZIP

The standard test for choosing between the PRM and ZIP models has been the Vuong test for non-nested models. After years of using this test, Desmarais and Harden (2013) and Wilson (2015) have shown, through Monte Carlo simulations, that the existing Vuong test does not provide any correction for additional parameters estimated in the inflation equation and is biased towards the zero-inflated models even in the absence of zero inflations in the data generation process. In solving this, the corrected versions of the Vuong test has been provided and includes all the functionalities of the old Vuong test but in reporting results, does so by presenting AIC-corrected, and BIC-corrected Vuong test statistics in addition to the uncorrected Vuong test (old version). It is the corrected version of the Vuong test that is used in deciding between the PRM and ZIP in this paper.

Empirical Model for the PRM and ZIP Regression

The first stage of the empirical process was to estimate model 1 for both PRM and ZIP models by regressing child labour on child labour-specific and household level variables. The corrected versions of the Vuong test was then used to choose the best-fit model (see Table 3 and Appendix 1). It can be seen from Appendix 1 that all the three criteria (uncorrected version, AIC-corrected, and BIC-corrected Vuong test statistics) are significant (at one percent) in favour of the ZIP model and also indicates that the child labour variable is over dispersed. Therefore, the use of the PRM technique will produce biased estimates. Based on this decision, I went on to estimate models 2 and 3 (using ZIP) for the rural and urban sub-samples to account for heterogeneity that might exist between rural-urban parents and child labour relations.

Model 1: pooled model

$$E(CL_i \mid X_i)_{full} = \delta_0 + \delta_1 \ln inc_i + \delta_2 \ln inc^2{}_i + \delta_3 agecl_i + \delta_4 femalecl_i + \delta_5 schcl_i + \delta_6 rural_i + \delta_7 agehd_i + \delta_8 poor_i + \delta_9 malehd_i + \delta_{10} eduhd_i + \delta_{11} oldmem_i + \delta_{12} reg_i + \varepsilon_i \tag{9}$$

Model 2: rural model

$$E(CL_i \mid X_i)_{rural} = \kappa_0 + + \kappa_1 \ln inc_i + \kappa_2 \ln inc^2{}_i + \kappa_3 agecl_i + \kappa_4 femalecl_i + \kappa_5 schcl_i + \kappa_6 agehd_i + \kappa_7 poor_i + \kappa_8 malehd_i + \kappa_9 eduhd_i + \kappa_{10} oldmem_i + \kappa_{11} reg_i + \eta_i \tag{10}$$

Model 3: urban model

$$E(CL_i \mid X_i)_{urban} = \lambda_0 + \lambda_1 \ln inc_i + \lambda_2 \ln inc^2{}_i + \lambda_3 agecl_i + \lambda_4 femalecl_i + \lambda_5 schcl_i + \lambda_6 agehd_i + \lambda_7 poor_i + \lambda_8 malehd_i + \lambda_9 eduhd_i + \lambda_{10} oldmem_i + \lambda_{11} reg_i + \gamma_i \tag{11}$$

where: *CL* is the number of child labourers; $\ln inc$ and $\ln inc^2$ are the logs of the fully composed household income and the square of it respectively; *agecl* is the age of the child; *femalecl* is a dummy for the female child; *schcl* is a dummy for the schooling status of the child; *agehd* is the age of the household head; *poor* is a dummy for the poverty status of the household; *malehd* is a dummy for the sex of the household head; *eduhd* is a categorical variable for the educational status of the household head; *oldmem* is the number of older household members; and *reg* captures regional dummies.

Results and Discussion

After choosing the ZIP model over the PRM based on the reported values for the uncorrected version, AIC-corrected, and BIC-corrected Vuong test statistics, I move on to present results with both incidence rate ratio (IRR) and the marginal effects for comparison purposes but the analyses are done using the marginal effects. The significant chow test (1% alpha level) indicates that the effect of income and other covariates on child labour is statistically different for the rural and urban cases so sub-sampled models for them better explain their peculiarities than a single model containing the locational effect. The goodness of fit test (McFadden's R^2) also shows that all the models are of good fit and they adequately estimate the effect of income on the number of child labourers in each household. One item to also consider is that, the number of child labourers in a household is inflated by whether the child is economically employed or not and also acts as the binary variable for regime one (R1). This variable is significant (1%) across models, indicating that economically employed children increase the probability of their parents increasing the number of child labourers in their households. It then justifies its use as the variable around which the inflation occurs.

The income variable across models (1) to (3) shows that the inverted-U that was observed for the non-parametric analysis has been confirmed by the ZIP model. Since the marginal effects indicate probabilities (due to maximum likelihood), I rely on this confirmation and invoke the outcome of the non-parametric analysis to indicate relative levels of altruism for rural and urban parents as regards child labour outcomes. The intuition here is that parents are non-altruistic at lower levels of income but at relatively higher levels, they become altruistic, not considering the leisure of their children as a cost. In specific terms the inverted-U evidence is realized at GH₵11,656.2760 ($5,834.26) for the total sample; GH₵11,308.3877 ($5,660.14) and GH₵22,026.4658 ($11,024.81) for the rural and urban sub-samples respectively. This resonates with the findings of Basu et al. (2010) and Lima et al. (2015) who found the inverted-U situation in India and Pakistan respectively but this study resolves the potential sample-selection bias that could emanate from the exclusion of the non-farm (urban) sample from the study.

Considering the age of the child labourer shows that by the time a child labourer becomes 20 years older, from a particular age, the probability of the household adding on another child labourer increases by 0.1. Specifically, the probability of increase resulting from the child labourer's age for the rural area is 0.08 while that of the urban area is also 0.1. As the children age, households require more resources thereby increasing more child labourers to cater for their resource-needs. Also, households' try to maintain their relative income levels by recruiting more child labourers to replace children who are exiting their child labour state.

Enrolling a child in school results in the probability of experiencing another incidence of child labour being 6 percent less than not enrolling the child in school. This situation is 8.5 percent for the rural area while it has no influence in the urban area. This means that education as a policy to reduce child labour will be more effective in the rural area than in the urban area because the child labourers in the rural areas are mostly used on the farm (Koomson & Asongu, 2016) and enrolling them in school takes them away from the farm, although they reckon that this could possibly result in a paradoxical effect of pushing the children into non-farm economic activities.

Table 3: Zero-Inflated Poisson Models for the effect of household income on Child labour

	(1)		(2)		(3)	
	Full Model		Rural Model		Urban Model	
Number of Child Labourers	IRR	Marginal Effect	IRR	Marginal Effect	IRR	Marginal Effect
Log (household income)	1.681***	0.402***	1.645***	0.504***	1.894***	0.226***
	(0.094)	(0.044)	(0.111)	(0.068)	(0.222)	(0.042)
Log (household income squared)	0.976***	-0.019***	0.978***	-0.023***	0.969***	-0.011***
	(0.003)	(0.002)	(0.004)	(0.004)	(0.006)	(0.002)
Age of child labourer	1.006**	0.005**	1.004	0.004	1.014**	0.005**
	(0.003)	(0.002)	(0.003)	(0.003)	(0.007)	(0.002)
Female child	1.007	0.006	1.013	0.013	0.955	-0.016
	(0.015)	(0.012)	(0.017)	(0.017)	(0.033)	(0.012)
School-going child (1=schooling; 0=not schooling)	0.925***	-0.060***	0.920***	-0.085***	0.895	-0.039
	(0.024)	(0.020)	(0.025)	(0.027)	(0.080)	(0.031)
Rural (1= rural, 0= urban)	1.146***	0.105***	—	—	—	—
	(0.029)	(0.020)	—	—	—	—
Age of household head	1.003***	0.002***	1.003***	0.003***	1.003**	0.001**
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Poor (1=poor, 0= not poor)	1.211***	0.148***	1.246***	0.222***	1.114**	0.038**
	(0.022)	(0.014)	(0.025)	(0.020)	(0.048)	(0.015)
Male household head (1=male, 0=female)	1.154***	0.111***	1.123***	0.118***	1.169***	0.055***
	(0.025)	(0.016)	(0.027)	(0.024)	(0.045)	(0.014)
Educational level of household head (Base=No education)						
Basic School	1.022	0.018	1.024	0.024	0.969	-0.012
	(0.019)	(0.015)	(0.021)	(0.021)	(0.047)	(0.019)

Table 3. *(Continued)*

Secondary School	0.884***	-0.093***	0.897***	-0.106***	0.829***	-0.068***
	(0.020)	(0.017)	(0.023)	(0.025)	(0.040)	(0.018)
Post-secondary and Tertiary	0.730***	-0.216***	0.909	-0.094*	0.543***	-0.183***
	(0.043)	(0.035)	(0.055)	(0.057)	(0.054)	(0.025)
Number of older household members	0.997	-0.003	0.991***	-0.009***	1.020**	0.007**
	(0.003)	(0.002)	(0.003)	(0.003)	(0.008)	(0.003)
Region (Base=Western)						
Central	1.311***	0.206***	1.366***	0.325***	1.241	0.059
	(0.079)	(0.049)	(0.090)	(0.076)	(0.163)	(0.039)
Greater Accra	0.945	-0.036	1.182	0.162	1.421***	0.103***
	(0.093)	(0.062)	(0.122)	(0.107)	(0.153)	(0.036)
Volta	1.229***	0.152***	1.197***	0.175***	1.398***	0.098**
	(0.047)	(0.028)	(0.049)	(0.040)	(0.162)	(0.038)
Eastern	1.221***	0.146***	1.043	0.038	1.903***	0.222***
	(0.044)	(0.026)	(0.042)	(0.037)	(0.113)	(0.021)
Ashanti	1.041	0.027	1.017	0.015	1.309***	0.076***
	(0.038)	(0.025)	(0.043)	(0.038)	(0.082)	(0.018)
Brong Ahafo	1.146***	0.097***	1.105***	0.093***	1.368***	0.090***
	(0.038)	(0.023)	(0.042)	(0.035)	(0.077)	(0.016)
Northern	1.085**	0.056**	1.074*	0.065*	1.109	0.027
	(0.041)	(0.026)	(0.045)	(0.038)	(0.087)	(0.021)
Upper East	1.166***	0.110***	1.059	0.053	1.839***	0.206***
	(0.042)	(0.026)	(0.042)	(0.035)	(0.133)	(0.028)
Upper West	1.362***	0.240***	1.330***	0.293***	1.434***	0.107***
	(0.049)	(0.027)	(0.052)	(0.038)	(0.145)	(0.034)
Constant	0.080***		0.105***		0.040***	
	(0.021)		(0.032)		(0.024)	
Inflate		.		.		.
Economically employed child < 15 years (1=yes, 0=no)	-29.272***	5.679***	-24.794***	6.001***	-26.350***	2.611***
	(0.033)	(0.088)	(0. 035)	(0.090)	(0. 077)	(0.113)
Constant	1.535***		1.182***		2.461***	
	(0. 029)		(0. 031)		(0. 067)	
Observations	19,147		12,587		6,560	
Nonzero observations	6,984		5,793		1,191	
Zero observation	12,163		6,794		5,369	
McFadden's R^2	0.274		0.235		0.366	
Wald-Statistic (χ^2)	691.75		528.21		310.51	
P-Value	0.000		0.000		0.000	
Log pseudolikelihood	-16644.1		-13326.59		-3004.61	
Chow test [LR chi2(21)]	231.60					
P-Value	0.000					
Vuong test: ZIP vs Standard Poisson	z = 45.96 (P>z = 0.000)					
AIC (Akaike) correction:	z = 45.94 (P>z = 0.000)					
BIC (Schwarz) correction:	z = 45.89 (P>z = 0.000)					

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Source: Author’s computation using GLSS6 data

Households in the rural areas are 10.5 percent more likely to add additional child labourers to their numbers than their counterparts in the big cities or urban areas. It is not surprising to see the rural households being likely to add more child labourers than urban households, because child labour, literary- and descriptive-wise (Tables 1 and 2) has been a rural phenomenon. By the time the household head gets ten years older, the probability of adding on another child labourer increases by 0.02 and this is 0.03 for a rural household while it is 0.1 for an urban household.

Male-headed households are 11.1 percent more likely to add on child labourers than female-headed households and considering the locational difference, male-headed households in the rural areas are more likely to add on child labourers than their rural counterparts. Education of the household head also plays a role in predicting the intensity of child labour at the household level. By inference, higher levels of education for the household head are associated with lower tendencies of adding on more child labourers. The educational effect is more pronounced in the urban area than in the rural area and this is expected because the urban-located parents, on the average, have higher levels of education than their rural counterparts.

Conclusion

This paper extended the literary discourse on the inverted-U in the parent-child labour relations to cover non-farm households and examined the effect of household income on the number of child labourers within households by controlling for other covariates. By covering non-farm households, the land size that has frequently been used as a proxy for wealth was replaced with a fully-composed household income that incorporates the value of land and five other components as income. This also resolved the potential problem of selection bias that could have emanated from zero values for land size that would have been recorded by non-farm households. Because the child labour variable was over dispersed and child labourers were mainly in the rural household, I settled on the zero-inflated Poisson (ZIP) model using both the uncorrected and corrected versions of the Vuong test and estimated rural and urban models to cater for the locational effect. I arrived at findings in support of the inverted-U empirics which suggest that parents are non-altruistic at lower levels of income but become altruistic at relatively higher levels of income. Higher incomes come with the ability to employ from outside the household and relieving the child of engagement in economic activities. More specifically I found that rural parents become altruistic at relatively lower levels of income than their urban counterparts. This outcome could be due to the relatively higher costs of living in the urban areas and big cities compared to the rural areas.

As the child labourers age, the probability of their homes adding more child labourers to their fold increases but the likelihood of occurrence is more in the urban area than in the rural area. Enrolling children in school also reduces the probability of adding more child labourers and the effect of education is mainly accounted for by parent-child labour relations in the rural areas than in the urban area since education of the child did not predict the intensity of child labour within urban households. Finally, rural-located households are 10.5 percent more likely to add on child labourers than urban households and this is because child labour is more of a rural phenomenon that an urban situation.

The government should increase its efforts at increasing the minimum wage for workers and provide a good price for agricultural products so that average household incomes will increase and result in parents being altruistic towards their children. Education should be made increasingly available and enforced as a necessity but should be designed as a holistic package. This can be explained in two folds: (1) the Free Compulsory Universal Basic Education (FCUBE) should be made fully operational and easily accessible so that it keeps children off the farm and other economic activities and when they become educated adults, it will also reduce the child labour numbers in households since educated household heads have been found to have less probabilities of increasing child labourers in their households. (2) a holistic education in the form of awareness creation of the adverse future impacts of child labour will curb the potential paradoxical effect of child labour-formal education policy that can drive children from the farm but leave them involved in non-farm economic activities after they close from school merely because they have become instruments for households' income diversification.

References

Afenyadu, D., 2010. Child labour in fisheries and aquaculture–a Ghanaian perspective, in: Background Paper Prepared for the Workshop on Child Labour in Fisheries and Aquaculture in Cooperation with the ILO. p. 15.

Baker, J.L., 2008. Urban poverty: A global view. Urban Pap. No -5, Washington, DC: World Bank.

Bandara, A., Dehejia, R., Lavie-Rouse, S., 2015. The impact of income and non-income shocks on child labour: evidence from a panel survey of Tanzania. World Dev. 67, 218–237.

Banerjee, A., Mullainathan, S., 2010. The shape of temptation: Implications for the economic lives of the poor. National Bureau of Economic Research.

Basu, K., Van, P.H., 1998. The economics of child labour. Am. Econ. Rev. 412–427.

Bauer, T.K., Sinning, M., 2010. Blinder–Oaxaca decomposition for Tobit models. Appl. Econ. 42, 1569–1575.

Bhalotra, S., Heady, C., 2003. Child farm labour: The wealth paradox. World Bank Econ. Rev. 17, 197–227.

Bhaskar, V., Gupta, B., 2012. Parental altruism and child labour: examining the historical evidence from the United States. Cliometrica 6, 249–266.

Boozer, M., Suri, T., 2001. Child labour and schooling decisions in Ghana. Manuscr. Yale Univ.

Cameron, A.C., Trivedi, P.K., 2010. Microeconometrics using stata.

Cockburn, J., 2002. Income contributions of child work in rural Ethiopia. University of Oxford, Centre for the Study of African Economies.

de Carvalho Filho, I.E., 2012. Household income as a determinant of child labour and school enrollment in Brazil: Evidence from a social security reform. Econ. Dev. Cult. Change 60, 399–435.

Desmarais, B.A., Harden, J.J., others, 2013. Testing for zero inflation in count models: Bias correction for the Vuong test. Stata J. 13, 810–835.

Dumas, C., 2007. Why do parents make their children work? A test of the poverty hypothesis in rural areas of Burkina Faso. Oxf. Econ. Pap.

Greene, W.H., 1994. Accounting for excess zeros and sample selection in Poisson and negative binomial regression models.

GSS, 2014. Ghana Living Standards Survey: Main Report. Ghana Statistical Service, Accra.

Gujaratı, D.N., 2004. Basic econometrics. McGraw-Hill New York.

Hashim, I., 2007. Independent child migration and education in Ghana. Dev. Change 38, 911–931.

Hilson, G., 2010. Child labour in African artisanal mining communities: Experiences from Northern Ghana. Dev. Change 41, 445–473.

Kambhampati, U.S., Rajan, R., 2006. Economic growth: A panacea for child labour? World Dev. 34, 426–445.

Koomson, I., Asongu, S.A., 2016. Relative Contribution of Child Labour to Household Farm and Non-Farm Income in Ghana: Simulation with Child's Education. Afr. Dev. Rev. 28, 104–115.
Kruger, D.I., 2007. Coffee production effects on child labour and schooling in rural Brazil. J. Dev. Econ. 82, 448–463.
Lambert, D., 1992. Zero-inflated Poisson regression, with an application to defects in manufacturing. Technometrics 34, 1–14.
Lima, L.R., Mesquita, S., Wanamaker, M., 2015. Child labour and the wealth paradox: The role of altruistic parents. Econ. Lett. 130, 80–82.
Rogers, C.A., Swinnerton, K.A., 2004. Does child labour decrease when parental incomes rise? J. Polit. Econ. 112, 939–946.
Siddiqi, F., Patrinos, H.A., 2002. Child labour: Issues, causes and interventions. HCOWP56. World Bank Work. Pap. Retrieved January 10 2002 Httpwww Worldbank Orghtmlextdrhnphddflashworkpwp00056 Html.
Vuong, Q.H., 1989. Likelihood ratio tests for model selection and non-nested hypotheses. Econom. J. Econom. Soc. 307–333.
Wilson, P., 2015. The misuse of the Vuong test for non-nested models to test for zero-inflation. Econ. Lett. 127, 51–53.
Winkelmann, R., 2013. Econometric analysis of count data. Springer Science & Business Media.

Appendix 1: Poisson and Zero-Inflated Poisson Regression Models for the effect of household income on Child labour

Number of Child Labourers	Poisson Coefficients	Zero-Inflated Poisson Coefficients
Log (household income)	0.921***	0.519***
	(0.088)	(0.056)
Log (household income squared)	-0.039***	-0.024***
	(0.005)	(0.003)
Age of child labourer	0.045***	0.006**
	(0.004)	(0.003)
Female child labourer (1=female; 0=male)	-0.013	0.007
	(0.022)	(0.015)
School-going child labourer (1=schooling; 0=not schooling)	-0.290***	-0.078***
	(0.035)	(0.025)
Rural (1=rural, 0=urban)	0.645***	0.136***
	(0.036)	(0.025)
Age of household	0.008***	0.003***
	(0.001)	(0.001)
Poor (1=poor, 0= not poor)	0.478***	0.192***
	(0.025)	(0.018)
Male household head (1=male, 0=female)	0.343***	0.143***
	(0.032)	(0.021)
Education level of household head (Base=No education)		
Basic School	0.018	0.022
	(0.027)	(0.019)

Appendix *(Continued)*

Secondary School	-0.406***	-0.123***
	(0.034)	(0.023)
Post-secondary and Tertiary	-0.837***	-0.315***
	(0.077)	(0.059)
Number of older household members	-0.093***	-0.003
	(0.005)	(0.003)
Region(Base=Western)		
Central	-0.317***	0.271***
	(0.082)	(0.060)
Greater Accra	-0.494***	-0.057
	(0.104)	(0.098)
Volta	0.309***	0.206***
	(0.056)	(0.038)
Eastern	0.394***	0.200***
	(0.053)	(0.036)
Ashanti	0.196***	0.040
	(0.054)	(0.037)
Brong Ahafo	0.508***	0.136***
	(0.049)	(0.033)
Northern	0.264***	0.081**
	(0.054)	(0.038)
Upper East	0.445***	0.154***
	(0.053)	(0.036)
Upper West	0.497***	0.309***
	(0.051)	(0.036)
Constant	-6.420***	-2.529***
	(0.404)	(0.261)
Inflate		
Economically employed child < 15 years		-29.272***
(1=yes, 0=no)		(0.033)
Constant		1.535***
		(0.029)
Vuong test: ZIP vs Standard Poisson		z = 45.96 (P>z = 0.000)
AIC (Akaike) correction:		z = 45.94 (P>z = 0.000)
BIC (Schwarz) correction:		z = 45.89 (P>z = 0.000)
Observations (N)	19,147	19,147
Nonzero observations		6,984
Zero observation		12,163
McFadden's R^2	0.135	0.274
Wald-Statistic (χ^2)	4002.63	691.75
P-Value	0.000	0.000
Log pseudolikelihood	-16644.1	-16644.1
Robust standard errors in parentheses		

*** p<0.01, ** p<0.05, * p<0.1

Source: Author's computation using GLSS6 data