The Joint Estimation of Child Participation in Schooling and Employment:

Comparative Evidence from Three Continents*

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ABSTRACT

This paper uses data from Peru, Pakistan and Ghana to simultaneously analyse child labour and child schooling, and compares them between these countries .We use a multinomial logit estimation procedure that analyses the participation and non participation of children in schooling and in employment and, in particular, allows the possibility that a child combines schooling with employment or does neither. We also use an ordered logit estimation procedure based on a ranking of the various child schooling/employment/non schooling/non employment outcomes. The results point to both similarities and striking dissimilarities in the nature of child labour and child schooling between the chosen countries. For example, in Pakistan, but not in Peru, the girl child's ordering of schooling/employment outcomes shows her at a position of extreme disadvantage.Household poverty discourages a child from achieving superior outcomes, but the effect varies markedly across the three countries.

JEL Classification:

C2, D1, I3, J2, O1

Keywords:

Child Employment, Household Poverty, Gender Divide,
Ordered Logit, Marginal Probability, Relative Risk Ratio

1. INTRODUCTION

The prominence accorded to the subject of child labour at the recent WTO meeting in Seattle is a reflection of its pivotal importance for the setting of international labour standards in an era of rapid globalisation. There have been calls to set up a multi-country organisation that might help design policies to reduce the incidence of child labour. Fallon and Tzannatos (1998) discuss ways in which the World Bank can assist member nations in reducing child labour.

Though the ILO (1996)'s estimates on labour force participation rates for children aged 10-14 years show a declining trend, in absolute terms the size of the child labour force is and will continue to be large enough to be of serious concern. There is no universal agreement on the magnitude of the child labour force, reflecting differences in the definition of child labour and in their measurement. According to the ILO (1996), 120 million children between the ages of 5-14 years have been engaged in full time paid work. If one includes part-time work as well, then the ILO (1996) estimate goes up to 250 million working children. The estimate of child labour would vary depending on how we define work, how we define a child, and how we collect the data, but few would disagree that this is a problem of gigantic proportions. In this study, we follow the ILO definition of child labour [see Ashagrie (1993)] in classifying a child as a 'labourer' if the child does full time, paid work. While this limits our analysis to only a subset of child work, it makes our study comparable with others in the literature[1].

Notwithstanding almost universal agreement that child labour is undesirable, there is wide disagreement on how to tackle this problem. The formulation of policies that are effective in curbing child labour requires an analysis of its key determinants, namely, identification of variables that have a significant effect on child employment. For example,

[1] In particular this ignores the huge number of children that work at home helping the adults in domestic activity (for example cooking, cleaning or taking care of children) or providing an additional hand in own farm activities.

Bonnet (1993) argues in the African context that poor quality of child schooling and their lack of apparent relevance to the child's employment skills encourage parents to take their children out of schools and put them into employment. The evidence presented in Ray (2000a) shows that the nature of child labour, its key determinants and, consequently, the strategies at reducing it, vary between countries. Child labour takes different form in different regions. Cross country comparisons, especially involving vastly different cultures and continents, enable better understanding of differences in the policies required to maximise their effectiveness in specific regional contexts. This paper extends Ray (2000a, 2000b) in using the unordered and ordered multinomial estimation procedures to analyse child participation in employment and schooling in Peru, Pakistan and Ghana. These countries, besides spanning a wide and diverse geographical area, provide considerable heterogeneity through their data sets to make this comparative study of considerable interest. For example, a sizeable percentage of children, especially girls, in Pakistan are neither in full time employment nor do they attend school, in marked contrast to Peruvian children, where the corresponding proportions are much smaller. Ghana provides an example of an intermediate case between Pakistan and Peru in that a significant proportion of her children combine employment with schooling, much more than in Pakistan but less than in Peru All of this prompts the need to undertake a comparative study of child labour on data sets involving vastly different countries and cultures. The present study, motivated by such an analysis, is in line with the recent empirical literature on child labour, that has focussed attention on the quantitative aspects taking advantage of the increasing availability of good quality data on child employment – see Grootaert and Kanbur (1995), Basu (1999) for surveys.

The point of departure of the present study from its predecessors lies in our use of a multinomial logit estimation strategy that simultaneously analyses child employment and child schooling. Nearly all the previous attempts [see, for example, Patrinos and

Psacharopoulos (1997), Psacharapoulos (1997), Jensen and Nielsen (1997), Ray (2000a)] have used a single equation based standard binomial logit model to analyse child labour and child schooling participation. The binomial logit estimation strategy recognises only two possibilities in a single estimation, namely, in case of child labour, the child either works or does not and, in case of schooling, either the child attends schooling or does not. In reality, however, there are simultaneously four possibilities to choose from: child (a) attends school but does not work, (b) works and attends school , (c) neither works nor attends school, and (d) works but does not attend school .While in South Asia, a sizeable proportion of children is in category(c), in Latin American countries, a large number of children combine employment with schooling as in category (b). The multinomial logit estimation strategy, that we adopt here, besides incorporating the simultaneity of decisions on child employment and child schooling, recognises these four mutually exclusive and exhaustive possibilities in identifying the key determinants of child labour and child schooling. In addition, we employ an ordered logit estimation procedure based on a natural ordering of the above mentioned categories from the viewpoint of the child's welfare. School only (category (a)) is the best outcome, work only (category (d)) is the worst outcome. Both school and work (category (b)) is the second best followed by neither school nor work (category(c)).

We also examine the role of community infrastructure by including community variables in the estimating regressions. The estimates allow an interesting comparison between countries on the impact of community infrastructure on the child's choice between the four possibilities mentioned above. The results are of considerable practical significance since the community variables provide potential instruments in devising effective policies that improve child welfare.

The rest of this paper is organised as follows. Section 2 discusses the estimation procedure. Section 3 describes the data sets, and compares some relevant child variables between the three countries. Section 4 presents and discusses the estimation results. In particular, Section 4.1 discusses the multinomial logit results and Section 4.2 discusses the ordered logit results. Concluding comments are presented in Section 5.

2. ESTIMATION METHODOLOGY

The decision to send a child to work is described by the following latent variable model.

$$W_i^* = X_{1i}\beta_1 + \varepsilon_{1i} \tag{1}$$

W_i^* is the net benefit attained by the family by sending child i to work, X_{1i} is a vector of child, family and community characteristics that determine W_i^*, and ε_{1i} is a random error, with zero mean and unit variance. However, W_i^* is not observed – what we do observe is the following binary variable:

$$W_i = \begin{cases} 1, \text{if the child works} \left(W_i^* > 0\right) \\ 0, \text{otherwise} \end{cases} \tag{1a}$$

Correspondingly, the decision to send a child to school is described by the following latent variable model:

$$S_i^* = X_{2i}\beta_2 + \varepsilon_{2i} \tag{2}$$

S_i^* is the net benefit to the family from sending the child to school, X_{2i} is the vector of child, family and community characteristics that determine S_i^*, and ε_{2i} is a random error with zero mean, unit variance. S_i^* is not observed – what we do observe is the following binary variable:

$$S_i = \begin{cases} 1, \text{if the child works} \left(S_i^* > 0\right) \\ 0, \text{otherwise} \end{cases} \tag{2a}$$

Equations (1) and (2) can be combined as follows:

$$\begin{pmatrix} W_i^* \\ S_i^* \end{pmatrix} = \begin{pmatrix} X_{1i} & 0 \\ 0 & X_{2i} \end{pmatrix} \begin{pmatrix} \beta_1 \\ \beta_2 \end{pmatrix} + \begin{pmatrix} \varepsilon_{1i} \\ \varepsilon_{2i} \end{pmatrix} \tag{3}$$

$$\text{ie. } Y_i^* = Z_i \beta + \varepsilon_i \tag{4}$$

where

$$Y_i^* = \begin{pmatrix} W_i^* \\ S_i^* \end{pmatrix}, Z_i = \begin{pmatrix} X_{1i} & 0 \\ 0 & X_{2i} \end{pmatrix},$$

$$\varepsilon_i = \begin{pmatrix} \varepsilon_{1i} \\ \varepsilon_{2i} \end{pmatrix} \text{ and } \beta = \begin{pmatrix} \beta_1 \\ \beta_2 \end{pmatrix}$$

The multinomial logit estimation procedure [see Greene (1993, chapter 21) for details] converts the latent variable model [eqn. (4)], via eqns. (1a, 2a), into an observable form (Y) involving the probabilities of the four States and then estimates the reduced form parameters using maximum likelihood procedure based on a multinomial logistic distribution of ε. These correspond to:

(i) $W_i^* \leq 0,\ S_i^* > 0$ (child does not work, attends school),

(ii) $W_i^* > 0,\ S_i^* > 0$ (child works and attends school),

(iii) $W_i^* \leq 0,\ S_i^* \leq 0$ (child neither works nor attends school) and

(iv) $W_i^* > 0,\ S_i^* \leq 0$ (child works, does not attend school).

Since the probabilities of being in the 4 States (i) – (iv) must add to unity for each child, the multinomial logit strategy involves estimating three equations. Note that the binomial logit estimation procedure adopted in Ray (2000a) and others, that we extend, is based on a binary choice variable involving a child's choice, in a given situation, between two states rather than four. In this study, we have normalised category (ii), ie. adopted the state of child working and attending school as the baseline case in the multinomial logit regressions. The multinomial logit model is given by:

$$\Pr ob.(Y = j) = \frac{e^{\gamma_j' z}}{1 + \sum_{k=1}^{3} e^{\gamma_k' z}} \qquad j=1,2,3 \tag{5}$$

$$\text{Prob}.(Y = 0) = \frac{1}{1 + \sum_{k=1}^{3} e^{\gamma_k' z}} \tag{6}$$

where γ_j is a vector of regression coefficients corresponding to choice outcome j, and outcome (ii) above is adopted as the base '0' for normalisation (ie. $\gamma_0 = 0$). The estimated equations [(5), (6)] provide a set of probabilities for the 4 employment/schooling choices for a child i with socioeconomic, demographic and community characteristics z. The binomial model used in, for example, Patrinos and Psacharopoulos (1997), Ray (2000b), is a special case of eqns. (5), (6) where j = 1. In other words, the present multinomial allows 4 choices rather than two in case of the binomial.

The coefficients in this model are difficult to interpret. The relative probability of Y = j in relation to the base category (Y = 0) is given by the 'relative risk' ratio, δ_j.

$$\delta_j = \frac{\text{Prob}.(Y = j)}{\text{Prob}.(Y = 0)} = e^{\gamma_j' z} \quad , j=1,2,3 \tag{7}$$

The ratio of the "relative risk" of choice j for a one-unit change in $\tilde{z}_i$, which is an element of Z, is $e^{\gamma_{ji}}$, where γ_{ji} is the parameter associated with characteristic $\tilde{z}_i$ in employment/schooling choice j. Thus, the exponentiated value of a coefficient is the relative risk ratio for a one unit change in the corresponding variable, it being understood that risk is measured as the risk of the category relative to the base category. Alternatively, the parameter estimates reported later measure the impact of a unit increase in the relevant explanatory variable on the log odds ratio of the particular state, in relation to the baseline category, namely, that the child combines employment with schooling. For example, if the estimated coefficient of the poverty variable (1, if the household is poor, 0, otherwise) is positive and significant for the state where the child works only, then this means that, relative to the case where the child works and attends school, the probability of the child working but not attending school is significantly higher in the case of children from poor households. While the binomial logistic procedure used in Ray (2000a) estimated the impact of poverty on child employment, it provided only an aggregated picture. The multinomial logistic procedure provides a disaggregated analysis that allows assessment of the impact of household poverty on the employment status of children in each of the three choice categories in relation to the baseline category.

The 4 choices mentioned above can be easily ranked in a descending order from the viewpoint of child welfare. Correspondingly, following Greene (1993, pgs. 672-673), we have the following ordered logit model.

$$y^* = \beta' Z + \varepsilon \tag{8}$$

where y^* is the child welfare corresponding to a given state of employment/schooling. As before, y^* is unobserved. What we do observe is:

$$\begin{aligned} y &= 0 \quad \text{if } y^* \le \mu_1 \\ &= 1 \quad \text{if } \mu_1 < y^* \le \mu_2 \\ &= 2 \quad \text{if } \mu_2 < y^* \le \mu_3 \\ &= 3 \quad \text{if } \mu_3 \le y^* \end{aligned} \tag{9}$$

The child welfare based ordering is as follows: only school (y = 0), both school and work (y = 1), neither school nor work (y = 2), only work (y = 3). The μ's (μ_1, μ_2, μ_3), referred to as "cut off points", are unknown parameters to be estimated along with β. As before, we assume that ε is normally distributed across observations. The coefficients, β, have an unambiguous interpretation only with respect to the two extreme states (y = 0, 3), not with respect to the middle ones (y = 1, 2). A negative coefficient estimate implies that, *ceteris paribus*, a unit increase in child characteristic z_i leads to a fall in the probability of the child only attending school (y = 0), and a rise in the probability of that child working only (y = 3).

Notice that, given the set of explanatory variables z_i, the probability of any observed outcome y = j, j = 0, 1, 2, 3 is given by:

$$\Pr(y_i = j|z_i) = F(\mu_{j+1} - z_i\beta) - F(\mu_j - z_i\beta)$$

so that the probabilities of the four observed outcomes in our model are:

$$\begin{aligned}
\Pr(y_i = 0|z_i) &= F(\mu_1 - z_i\beta) \\
\Pr(y_i = 1|z_i) &= F(\mu_2 - z_i\beta) - F(\mu_1 - z_i\beta) \\
\Pr(y_i = 2|z_i) &= F(\mu_3 - z_i\beta) - F(\mu_2 - z_i\beta) \\
\Pr(y_i = 3|z_i) &= 1 - F(\mu_3 - z_i\beta)
\end{aligned}$$

3. DATA AND DESCRIPTIVE STATISTICS

The child labour data for the study came from the Peru Living Standards Measurement Survey (PLSS) in 1994, the Pakistan Integrated Household Survey (PIHS) in 1991, and the Ghana Living Standards Measurement Survey (GLSS) in 1988/89. These surveys were conducted jointly by the respective governments and the World Bank as part of the Living Standards Measurement Study (LSMS) household surveys in a number of developing countries[2]. The purpose of the LSMS surveys is to provide policy makers and researchers with individual, household and community level data needed to analyse the impact of policy initiatives on living standards of households. The Pakistan Integrated Household Survey covered 4800 households, the Peru Living Standards Survey involved 3623 households, and the Ghana Living Standards Survey involved 3192 households. While the Peruvian sample contained information on child labour and child schooling of 5231 children aged 6 – 17 years, the Pakistani data set yielded 5866 observations on children aged 10 –17 years, and the

[2] See Grosh and Glewwe (1995) for an overview and general description of the LSMS data sets.

Ghanian sample on 5245 children aged 7 –17 years. Some of these observations could not be used, however, because of poor quality.

The household's poverty status[3], which was one of the economic determinants of child labour and child schooling, was defined over non-child household income. This avoids the possible endogeneity of the poverty variable since household income, net of child labour earnings, is unlikely to be endogenous in an equation that explains child labour. This reflects the assumption that decisions on child labour are taken *after* adult and other non-child earnings are determined. Such a view, also, underlies the 'Luxury Axiom' of Basu and Van (1998), namely, that a family will send the child to the labour market only if the family's income from non child labour sources drops very low.

Table 1 contains description of the variables used in this study. Tables 2A – 2D present comparative figures, for the 3 countries, of the percentage of children belonging to the 4 mutually exclusive and exhaustive employment/schooling states considered in this study. The figures, which also provide information on the gender differential, show some interesting dissimilarities and similarities between the three countries. First, a sizeable proportion of Pakistani and Ghanian children is neither in employment nor in school. In contrast, the corresponding proportion of Peruvian children who belong to this category is considerably smaller. The large numbers of Pakistani children in this category is typical of the entire South Asian region [see Weiner (1996)]. Ravallion and Wodon (2000)'s recent observation that a targeted enrolment subsidy in rural Bangladesh increased schooling by far more than it reduced child labour is, perhaps, explained by the fact that a large number of children, who were previously neither in employment nor in schooling, enrolled as a result of this subsidy. It is, perhaps, not unreasonable to expect a large number of these children to be involved in domestic duties. On this interpretation, the gender differential in favour of higher proportion

[3] The poverty line was set at 50% of the median sample of per adult equivalent non child household income.

of girls, vis a vis boys, involved in domestic duties exists in all countries. However, the size and statistical significance of such gender imbalance is nowhere as large or as pronounced as that in Pakistan. The actual gender differential will be still greater in Pakistan than these figures suggest since a girl that goes neither to work nor to school is much more likely to be helping out with household chores than her brother in the same category. Second, the gender imbalance in Pakistan in domestic duties reverses itself for older children (15 – 17 years) in the direction of greater participation by boys as we move to the category of full time, "economically active" children – more boys work than girls. The Pakistani experience is not, however, shared by Peruvian or Ghanian children. Third, as noted in Patrinos and Psacharopoulos (1997), Ray (2000a), a much higher proportion of Peruvian children combine employment with schooling than in other countries. There exists a pronounced and large gender differential in favour of Pakistani and Peruvian boys in this category. It is, also, worth noting that in Ghana, though not in Pakistan, the proportion of children, especially boys, who combine employment with schooling rises quite sharply in the later age categories. Third, in case of pure school going children with no work involvement, while the enrolment rate in Peru starts to decline markedly only beyond 13 years, in case of Pakistan and Ghana the enrolment rate peaks around 11 and 9 years, respectively, and falls to alarmingly low levels, especially for older girls. Fourth, the schooling participation rates of Peruvian children in all age groups are considerably higher than their Pakistani and Ghanian counterparts. Moreover, the gender bias in favour of boys schooling in Pakistan contrasts sharply with a more even gender balance in case of Ghana and a reversal in favour of girls' schooling in case of Peru.

Table 2E presents, for each child age group, joint tests for the equality of mean vectors between boys and girls in the four categories. A more generalised version of the standard t-tests for the equality of means between groups is Hotelling's T-squared test [see Scott Long (1997)]. This allows us to test the joint hypothesis that the average participation rate in all the categories is the same between boys and girls. The Hotelling's T-squared statistic is given by $T^2 = (\bar{x}_1 - \bar{x}_2)S^{-1}(\bar{x}_1 - \bar{x}_2)$ where $\bar{x}_1, \bar{x}_2$ are the mean vectors, and S is the estimated covariance matrix. This in turn gives us the following test statistic: $F = \frac{(n-k-1)}{(n-r)k}T^2 \sim F(k, n-k-1)$, where k is the number of categories (k = 4 here), n is the number of observations, and r is the number of groups (r = 2 here). The results are presented in Table 2E.

Pakistan stands out with respect to gender differential. Not only is the equality of mean vectors between boys and girls rejected in case of Pakistan for each of the age groups for which data is available, but the margin of rejection as reflected in the magnitude of the T^2 statistic is much higher there than in the other two countries. Two other features are, also, worth noting: (a) unlike in Pakistan, equality of gender means is not rejected in Peru or Ghana in the younger child age groups (6 – 10 years), and (b) in the older age groups (16, 17 years), Peru overtakes Ghana with respect to the magnitude of the differential between the boys and girls mean vectors.

Further evidence on the difference between the nature of child labour in the three countries is contained in Table 3, which presents the share of household income contributed by child labour earnings. The following features are worth noting. First, the Peruvian household is much less dependent on child labour earnings than its counterpart in Pakistan or Ghana. Second, as we move from children who only work to those who combine schooling with employment, the share of child labour earnings in household income drops in all cases. Note, however, that the drop is the least in case of Peruvian girls suggesting that schooling has relatively little impact on their ability to contribute to the household income through their labour earnings. Third, the sizeable proportion of household income that comes from child labour, especially in Pakistan and Ghana, points to the high vulnerability of several households to poverty, if their access to child labour earnings is reduced or removed through legislation[4] without corresponding improvement in credit availability or the employment opportunity of their adults.

4. RESULTS

4.1 Multinomial Logit Estimation Results

Tables 4 – 6 present the multinomial logit regression estimates for, respectively, the following child's employment/schooling choices: (a) attends school but does not work (Table 4), (b) works but does not attend school (Table 5), (c) neither attends school nor works(Table 6). As mentioned earlier, the choice category where the child attends school and works, ie. combines schooling with employment, has been adopted as the baseline category for normalisation. Each of these tables presents the results for Pakistan, Ghana and Peru in a form that allows ready comparison between the country estimates. While such comparison is possible for the coefficients of most of the child and household variables, the community coefficients are non comparable because of differences in their definition between the three data sets.

The following results are implied by the tables:

(i) In all these countries, older children are more likely to combine schooling with employment than younger children. This is seen from the significantly negative estimate of the child age coefficient in each of the nine cases presented in these three tables. A comparison of the tables shows that, for each country, the absolute magnitude of the estimated age coefficient is highest in case of category (c). This means that, as the child grows older, the inflow into the base category where the child combines schooling with employment is the highest from those who are engaged in neither activity. The positive age square coefficient suggests, however, that this inflow weakens in the higher age groups.

(ii) The gender coefficient is positive and mostly significant suggesting that girls are more likely than boys to specialise in either schooling or in employment or do neither than in combining the two activities.

(iii) Differences exist between countries with respect to the region of residence variable. For example, Table 5 shows that the urban child in Ghana is *less* likely to specialise in work, *more* likely to combine schooling with employment. The exact reverse is

[4] Basu (2000) has, recently, explored the sensitivity of child labour earnings vis a vis adult earnings to movements in the adult minimum wage.

indicated for Peru. Table 6 shows that in Peru, with urbanisation, a child engaged in both schooling and employment tends to withdraw from both. Neither of the other two countries shares this result.

(iv) Household composition, generally, does not exert a significant impact on the child's schooling/employment decision and, where it does, it is through the number of adults rather than the number of children in the household. In Peru and Ghana, though not in Pakistan, an increase in the number of adults in the household leads to children withdrawing from both schooling and employment (Table 6).

(v) The gender of the household head matters in Ghana (Tables 4, 5), but not much in the other countries.

(vi) Of particular interest in these calculations are the estimated coefficients of the poverty and per adult equivalent expenditure variables. Though both these variables measure the changing economic circumstances of the household, the former refers to a discrete effect due to the household crossing the poverty line, while the latter measures the propensity of the child to change states due to small changes in the continuous expenditure variable[5]. There are some interesting differences between the country estimates of these effects. For example, Tables 5, 6 show that, when a Pakistani household falls into poverty, there is a strong tendency for a child that was combining schooling with employment to, either, specialise wholly in the latter, or to withdraw completely from both activity, possibly, to do domestic chores. This is consistent with the prediction of the 'Luxury Axiom' of Basu and Van (1998) and with the previous Pakistani evidence contained in Ray (2000a, 2000b). Note, however, that such a "poverty effect" on child behaviour is non existent in Peru and, at best, a weak one in the Ghanian case.

(vii) With increasing education of the adult female in the household, there is a strong tendency for the child in Ghana, less so in Pakistan and Peru, to move out of the 'work only' and 'neither in school nor in work' categories to one where she/he combines schooling with employment (Tables 5, 6).

(viii) The coefficients of the adult wage variables show the nature of interaction between the adult and child labour markets. As the recent analysis of Basu (2000) shows, the nature of such interaction determines the effectiveness of minimum wage legislation in reducing the incidence of child labour. The tables show that, in general, the impact of adult wages on the child's choice of categories is larger in Pakistan than in the other countries. In Pakistan, an increase in female wages leads to a significant movement from each of the three choice categories, depicted in Tables 4 – 6, to the base category where the child combines schooling with employment. The movement out of category (a) ("school only") and category (c) ("neither in school nor in work"), consequent on an increase in female wages, is the disaggregated picture underlying the complementarity between the adult female and child labour markets observed in Pakistan using the binomial logit estimation procedure in Ray (2000a). Note that, unlike female wages, movement in Pakistani male wages, does not have any impact on children who are exclusively in schooling (Table 4). Nor do adult wage movements in Ghana or Peru have much of an impact on children who specialise in either activity (Tables 4, 5). It is worth emphasising from these results that the complementarity between the adult female and child labour markets is quite unique to Pakistan.

[5] It is incorrect to argue, as Bhalotra (1999) does, that a positive poverty coefficient merely implies that child labour is an inferior item. Such a view reflects non recognition of the distinction between the continuous and discrete effects.

(ix) Jafarey and Lahiri (2000) have, recently, systematically explored the link between credit markets and child labour. The Pakistani and Ghanian data sets provide information on the amount of money lent and borrowed by the households. The effects, even when they are statistically significant, are weak. The relative risk ratio is unity for the credit coefficients, thus, denying a strong link between credit variables and child labour. We have not, in this study, attempted a formal test of the relationships between credit markets and child labour, discussed in Jafarey and Lahiri (2000), since it requires an estimation framework that treats a household's credit market behaviour and child labour as jointly endogenous. While such an exercise is beyond the scope of the present study, it is a useful area for further research, especially since the nature of the relationship, if any, between credit markets and child labour is of considerable policy significance.

(x) Community variables have significant effects in several cases. For example, the provision of improved electricity facility in Peru encourages schooling at the expense of employment (Tables 4, 5), while the provision of improved water supply facilities in Peru encourage children to combine schooling at the expense of exclusive work or exclusive school. The community variables also exert strong impact on the child's choice of categories in Ghana. Improvements in communal facilities encourage children who are specialising in work or doing neither activity to combine schooling with employment. The Pakistani data set provides additional information on the availability of schools in the cluster of residence of the child. The availability of girls schooling and an increase in their number in the neighbourhood encourage Pakistani children who are neither in employment nor in schooling to take up both. The presence of primary schools in the neighbourhood has a similar effect in Ghana (Table 6).

Table 7 presents the marginal probabilities, implied by the multinomial logit estimates of Table 4 – 6, of the four choice outcomes for a selection of comparable variables between countries. The marginal probabilities, which are easier to interpret, show the marginal changes in the probabilities of the four outcomes, when the corresponding child, household or community characteristic changes by one unit. The estimates allow ready comparison between countries. Consistent with the previous discussion, in all these countries, older children are *more* likely to combine schooling with employment, and *less* likely to be doing neither, with the child age effect proving strongest in Ghana. Again, in all these countries, girls are more likely than boys to be neither in schooling nor in employment, and less likely to combine schooling with employment. In Pakistan and Ghana, girls are much less likely than boys to be exclusively in schooling with no outside work involvement, while the exact reverse, though not as strongly, is indicated for Peru. In all the three countries, household poverty tends to have a detrimental effect on pure school going children, though in varying degrees, the strongest being in Ghana, the weakest in Peru. These countries, also, agree that household poverty encourages children to migrate to the “work only” category. However, differences exist between countries with respect to the ‘poverty effect’ on the other choice categories. There is wide agreement between countries on the impact of urbanisation or the child’s choice of categories – the urban child is more likely than the rural to be in the “school only” category, though the urbanisation effect is not as strong in Ghana. The community variables, whose marginal probabilities will be made available on request have, mostly though not always, the expected impact by encouraging children to concentrate on schooling and discouraging them from choosing a “work only” outcome. The base probabilities confirm the higher priority that Peruvian parents attach to their children’s education, since a much larger percentage of children in Peru are purely school going or combine schooling with employment than in Pakistan or Ghana.

4.2 Ordered Logit Estimation Results

Table 8 presents the corresponding marginal probabilities implied by the ordered logit estimates. The latter, ie. the coefficient estimates and the standard errors, are presented in the Appendix (Table A1). The outcomes, it may be recalled, are arranged in a decreasing order from the viewpoint of child welfare. The base probabilities in Peru show that the probability based ordering of the four outcomes coincide with that based on child welfare – for example, the Peruvian child is most likely to choose the best outcome, the least likely to choose the worst outcome. The ordering of the intermediate outcomes in Pakistan and Ghana are inconsistent with their child welfare ordering. The second highest base probability attached to the third outcome reflects the high percentage of children in Pakistan and Ghana who are neither in school nor in employment. With respect to the sign and magnitude of the marginal probabilities, Pakistan and Ghana are closer to one another than to Peru. The gender effect is particularly strong in Pakistan placing the girl child there in a position of disadvantage vis a vis Pakistani boys in trying to attain the most desirable outcome. The ordered logit estimates show [see Table A1] that an increase in the number of girls' schools in the cluster in Pakistan or the presence of primary schools in the neighbourhood in Ghana has strong beneficial effects in helping the child attain the most desirable outcome. The ordered logit estimates also show that in both Pakistan and Ghana, children from households whose head speaks the dominant language are at an advantage in tyring to achieve the "best" outcome (ie. "school only").

Table 9 presents the ordered logit coefficient estimates on combined country data obtained by pooling comparable variables over the 3 countries. The ordered outcomes, as above, are arranged in decreasing order of child welfare with the "school only" category the "best" outcome, and the "work only" the worst. Taking Peru to be the base country , we allow country dummies for Pakistan and Ghana, and their interactive effects with household poverty and gender of the child. The estimates confirm strong country effects in the estimated regressions. The advantage of pooling the data is evident from the high statistical significance recorded for all the parameter estimates. Household poverty pushes the child away from the "best outcome" (school only) in the direction of the "worst " (work only). In contrast, children from female headed households and from those with highly educated adult females are much more likely than others to achieve the "best" outcome. The urban child is, *ceteris paribus*, better placed than the rural child in achieving the most preferred outcome. The coefficient estimates of the dummy interactive terms, which are all highly significant, show that the "poverty effect" is enhanced in both Pakistan and Ghana, while the "child gender" effect is magnified many fold in Pakistan. An increase in the number of adults in the household helps the child in attaining the “school only” outcome, but an increase in the number of children has an opposite effect.

The ordered logit coefficient estimates do not allow unambiguous statements on the intermediate outcomes. Table 10 presents the marginal probabilities implied by the ordered logit estimates on combined country data. The country dummy marginal probabilities show that, *ceteris paribus*, a Ghanian child is more likely to achieve inferior outcomes and the least likely to achieve the “best” outcome compared to the others. Household poverty worsens her plight still further, so that a poor Ghanian child has 25% less probability of achieving the “best” outcome, and 9% more probability of ending up with the “worst” outcome than a non poor child from the other two countries. Girls are more likely than boys in Peru to achieve the “best” outcome. However, the country/gender interactive coefficient estimates show that this picture changes completely for other countries, especially Pakistan. The Pakistani girl fares the worst in relation to others in achieving satisfactory outcomes. Urbanisation, female headship of the household and increasing education of the adult female all help in the child achieving the most desirable outcome, ie. attends school with no outside work involvement.

The base probabilities show that, on “revealed preference”, while the three countries as a group rank the “school only” outcome as the best, and the “work only” outcome as the worst, the ranking of the two intermediate outcomes is at variance with that implied by child welfare. Note, also, that the gap between the base probabilities of the intermediate outcomes and, consequently, the inconsistency with the implications of child welfare is higher in Pakistan and Ghana than in Peru. Household poverty worsens the situation further, especially for the girl child in these countries. For example, in case of a Pakistani girl child belonging to a poor household, the “school only” outcome becomes the least preferred, and the “neither in school nor in work” the most preferred outcome. This confirms the strong impact that household poverty exerts on the girl child in Pakistan in withdrawing her from schooling and keeping her at home to help out with activities which are not officially recognised as "work" in the ILO based definition adopted in this study.

5. CONCLUSION

The issue of child labour, which is at the heart of the development literature today, has attracted considerable attention in recent years. Notwithstanding continuous and significant reductions during much of the previous century, the child labour force is still large enough to be of serious concern. Strategies aimed at reducing or eliminating child labour need, for their effectiveness, identification of its key determinants. A comparative study of child labour on disparate data sets, using a common estimation framework, is therefore of considerable policy importance. Such a study has been the principal motivation of this exercise. This paper uses high quality, comparable data from countries located in different continents to compare and analyse the phenomenon of child labour in these regions. The chosen countries, Peru, Pakistan and Ghana, provide considerable heterogeneity through their data sets to make the results of this study significant.

Methodologically, this study departs from much of the existing literature in using a multinomial logit estimation procedure that simultaneously analyses the participation and non participation of children in schooling and in employment. In doing so, the study recognises that the child has four possibilities to choose from: she/he (i) attends school but does not work, (ii) works and attends school, (iii) neither works nor attends school, and (iv) works but does not attend school. The binomial logit estimation procedure, that much of the previous empirical literature is based on, views work and schooling as mutually exclusive and, moreover, does not recognise, let alone analyse, the outcome that the child is neither in schooling nor in employment. While many Peruvian children combine schooling with employment, a large number of children in South Asia are in neither activity. In extending the conventional binomial approach, the multinomial logit estimation procedure accommodates all the four mutually exclusive and exhaustive outcomes mentioned above. Two other methodological features of this study are worth noting: (a) use of an ordered logit estimation procedure based on a ranking of the four outcomes in decreasing order of child welfare, and (b) estimation on the combined country data using a selection of common, comparable variables. The latter, which allows for heterogeneity between the data sets through a set of dummies, brings into sharp focus some key differences between the countries in relation to the child's choice of the schooling/employment outcomes.

The principal results can be summarised as follows:

(i) All the three countries agree that (a) older children are *more* likely to combine schooling with employment than younger children, (b) girls are *less* likely than boys to combine schooling with employment, and *more* likely to be doing neither, and (c) increasing awareness, through education, of the adult female combined with improved communal facilities, especially provision of schools in the neighbourhood, significantly reduce child labour.

(ii) Strong differences exist between the chosen countries in other respects relating to child labour. For example, household poverty in Pakistan discourages a child from combining schooling with employment and encourages her/him to either specialise in employment or concentrate on domestic duties. Such a "poverty effect" on child behaviour is non existent in Peru and, at best, a weak one in Ghana. The Pakistani data is, also, distinctive in that, unlike in the other two countries, an increase in female wages there leads to a significant movement from each of the three choice categories to the base category where the child combines schooling with employment. This close nexus between the child and adult female labour markets seems to be quite a unique feature of the Pakistani data set.

(iii) The ordered logit estimation results highlight the gender divide that characterises child behaviour in Pakistan and, to a lesser extent, Ghana, but hardly visible in Peru. The base probabilities show that, abstracting from country, child gender, household poverty and other attributes, a child is *most* likely to choose the best outcome ("school only") and the *least* likely to choose the *worst* outcome ("work only"). However, the introduction of interactive dummies involving country, household poverty and child gender, leads to a large deviation from this benchmark. For example, for a "poor" girl child in Pakistan, the "school only" outcome becomes the least preferred, and the "neither in school nor in work" the most preferred outcome. More generally, the ordered logit results show that household poverty pushes the child away, though in varying degrees between countries, from the best outcome ("school only") in the direction of the worst outcome ("work only"). Moreover, an increase in the number of adults in the household helps the child in attaining the “school only” outcome, but an increase in the number of children has an opposite effect.

The central message of this exercise is that one needs to recognise the regional diversity in the nature of child labour in formulating policies to reduce or eliminate it. For example, while improved provision of good quality schools helps to reduce child labour everywhere, such schools need to be located near places of child employment in Peru, and in the residential neighbourhood in Pakistan. This recognises the fact that, while Peruvian children tend to combine schooling with employment, large numbers of Pakistani children, especially girls, are at home doing neither. The Pakistani results also highlight the need to target households living below the poverty line and, especially, girls in such households for effective child welfare enhancing policies. Moreover, in Pakistan, steps need to be directed at breaking the close nexus that exists there between the adult female and the child labour markets.

While the overall goal of such policies must be to move the child from a “work only” to “school only” status, such a strategy can only be a long term one. In the short run, any policy that moves a child from a “work only” or “neither in work nor in school” status to one where she/he combines schooling with employment must be considered to be a significant success. This prompts the need to widen the definition of child work to include domestic hours and other forms of non remunerative child work.

Table 1: Description of Variables

Variable	Description
AGE	Age of Child
AGE2	Age of Child Squared
GIRL*	Gender of Child (1 = girl, 0 otherwise)
URBAN*	Region of Residence (1 = urban, 0 = rural)
NCHILD	Number of Children in Household
NADULT	Number of Adults in Household
AMOUNTL	Amount Lent (Pakistan, Ghana)
AMOUNTB	Amount Borrowed (Pakistan, Ghana)
FHH*	Gender of Household Head (1 = female, 0 = male)
HEADAGE	Age of Household Head
LANGHH*	Language of Household Head (1 = Dominant Language, 0 otherwise)
MAXFEMED	Number of years of Schooling of the Most Educated Female in the Household
WATER1*	= 1 If Household has Access to Piped Water, 0 otherwise (Pakistan only)
ROAD	= 1 if Road is available, 0 otherwise (Pakistan only)
CLOSEDDR*	= 1 if Closed Drains near House, 0 otherwise (Pakistan only)
DISPOS1*	= 1 if Household has no Waste Disposal Method, 0 otherwise (Pakistan only)
DWATER*	= 1 if the Main Source of Drinking Water is River, Lake, Spring or Pond, 0 otherwise (Ghana only)
TOILET*	= 1 if Toilet Facility for the Household is Pit Latrine, 0 otherwise (Ghana only)
LIGHT*	= 1 if Main Source of Lighting for the Household is Kerosene, Oil or Gas Lamp, 0 otherwise (Ghana only)
ELECTR*	= 1 if Main Source of Illumination is Electricity, 0 otherwise (Peru only)
WATER2*	= 1 if Water Supply is Inside the House, 0 otherwise (Peru only)
WATERC*	= 1 if water is not Contaminated, 0 otherwise (Peru only)
DISPOS2*	= 1 if Main Form of Waste Disposal is Public Connection Inside House, 0 otherwise (Peru only)
BOYSC	Number of Boys Schools in Cluster (Pakistan only)
GIRLSC	Number of Girls Schools in Cluster (Pakistan only)
COEDSC	Number of Coeducation Schools in Cluster (Pakistan only)
BOYCLOS*	= 0 if any Boys School in Cluster is Closed, 1 otherwise (Pakistan only)
GIRLCLOS*	= 0 if any Girls School in Cluster is Closed, 1 otherwise (Pakistan only)
COEDCLOS*	= 0 if any Coeducation School in Cluster is Closed, 1 otherwise (Pakistan only)
PRIMYES*	= 1 if there is any Primary School in Cluster, 0 otherwise (Ghana only)
POV*	= 1 if Household is Poor, 0 otherwise
PCEX	Expenditure Per Equivalent Adult
MAXMWAGE	Maximum Wage Earned by Male Members in the Household
MAXFWAGE	Maximum Wage Earned by Female Members in the Household
MAXFWAGE2	Maximum Female Wage Squared

Note: * denotes a dummy variable.

Table 2A: Percentage of Children Who Attend School and Do Not Work

	Peru				Pakistan				Ghana			
Age	**Overall**	**Boys**	**Girls**	**Difference**	**Overall**	**Boys**	**Girls**	**Difference**	**Overall**	**Boys**	**Girls**	**Difference**
6	0.797	0.817	0.774	.043	-	-	-	-	0.5	0.504	0.496	0.008
7	0.808	0.792	0.825	-.033	-	-	-	-	0.619	0.647	0.594	0.053
8	0.816	0.788	0.840	-.052	-	-	-	-	0.559	0.591	0.524	0.067
9	0.796	0.777	0.814	-.037	-	-	-	-	0.614	0.631	0.596	0.035
10	0.707	0.679	0.735	-.056	0.591	0.698	0.478	0.220*	0.583	0.609	0.554	0.055
11	0.704	0.674	0.738	-.064	0.637	0.734	0.522	0.212*	0.518	0.535	0.500	0.035
12	0.649	0.594	0.703	-.109*	0.544	0.627	0.443	0.184*	0.471	0.496	0.438	0.058
13	0.662	0.654	0.669	-.015	0.499	0.577	0.428	0.149*	0.404	0.420	0.385	0.035
14	0.559	0.494	0.623	-.129*	0.439	0.527	0.356	0.171*	0.397	0.381	0.417	-0.036
15	0.523	0.472	0.574	-.102*	0.376	0.450	0.295	0.155*	0.315	0.387	0.241	0.146*
16	0.490	0.475	0.505	-.030	0.336	0.402	0.270	0.132*	0.266	0.311	0.222	0.089*
17	0.365	0.311	0.416	-.105*	0.324	0.358	0.278	0.080*	0.220	0.254	0.179	0.075

Note: * denotes that the gender difference is statistically significant at 5% significance level.

Table 2B: Percentage of Children Who Attend School and Work

	Peru				Pakistan				Ghana			
Age	**Overall**	**Boys**	**Girls**	**Difference**	**Overall**	**Boys**	**Girls**	**Difference**	**Overall**	**Boys**	**Girls**	**Difference**
6	0.081	0.071	0.092	-0.021	-	-	-	-	-	-	-	-
7	0.115	0.121	0.109	0.012	-	-	-	-	0.032	0.027	0.036	-0.009
8	0.123	0.156	0.096	0.060*	-	-	-	-	0.066	0.087	0.044	0.043*
9	0.177	0.186	0.169	0.017	-	-	-	-	0.087	0.097	0.076	0.021
10	0.237	0.281	0.196	0.085*	0.054	0.074	0.033	0.041*	0.125	0.133	0.116	0.017
11	0.253	0.302	0.200	0.102*	0.060	0.088	0.027	0.061*	0.191	0.221	0.159	0.017
12	0.288	0.338	0.238	0.100*	0.081	0.108	0.048	0.060*	0.161	0.176	0.143	0.033
13	0.242	0.290	0.199	0.091*	0.083	0.147	0.025	0.122*	0.199	0.203	0.195	0.008
14	0.310	0.376	0.246	0.130*	0.088	0.143	0.035	0.108*	0.212	0.274	0.129	0.145*
15	0.294	0.377	0.213	0.164*	0.081	0.119	0.040	0.079*	0.202	0.247	0.155	0.092*
16	0.267	0.337	0.201	0.136*	0.058	0.105	0.011	0.094*	0.201	0.220	0.182	0.038
17	0.203	0.302	0.111	0.191*	0.077	0.130	0.005	0.125*	0.150	0.204	0.080	0.124*

Note: * denotes that the gender difference is statistically significant at 5% significance level.

Table 2C: Percentage of Children Who Do Not Attend School but Work

	Peru				Pakistan				Ghana			
Age	**Overall**	**Boys**	**Girls**	**Difference**	**Overall**	**Boys**	**Girls**	**Difference**	**Overall**	**Boys**	**Girls**	**Difference**
6	0.014	0.007	0.021	-0.014	-	-	-	-	-	-	-	-
7	0.010	0.017	0.004	0.013	-	-	-	-	0.021	0.036	0.008	0.028*
8	0.016	0.013	0.018	-0.005	-	-	-	-	0.045	0.045	0.044	0.001
9	0.002	0.005	0.000	0.005	-	-	-	-	0.048	0.055	0.040	0.015
10	0.011	0.014	0.009	0.005	0.113	0.074	0.154	-0.080*	0.083	0.089	0.076	0.013
11	0.011	0.008	0.013	-0.005	0.118	0.073	0.169	-0.096*	0.119	0.111	0.128	0.017
12	0.030	0.038	0.021	0.017	0.161	0.147	0.178	-0.031	0.148	0.149	0.148	0.001
13	0.042	0.023	0.059	-0.036*	0.171	0.154	0.188	-0.034	0.181	0.232	0.118	0.114*
14	0.075	0.089	0.061	0.028	0.234	0.218	0.249	-0.031	0.204	0.163	0.258	-0.095*
15	0.100	0.104	0.097	0.007	0.269	0.279	0.258	0.021	0.257	0.216	0.299	-0.083*
16	0.113	0.109	0.117	-0.008	0.330	0.407	0.253	0.154*	0.300	0.259	0.341	-0.082
17	0.182	0.236	0.132	0.104*	0.312	0.354	0.254	0.100*	0.343	0.324	0.366	-0.042

Note: * denotes that the gender difference is statistically significant at 5% significance level.

Table 2D: Percentage of Children Who Neither Attend School Nor Work

	Peru				Pakistan				Ghana			
Age	Overall	Boys	Girls	Difference	Overall	Boys	Girls	Difference	Overall	Boys	Girls	Difference
6	0.019	0.105	0.113	-0.008	-	-	-	-	0.500	0.496	0.504	-0.008
7	0.066	0.071	0.061	0.010	-	-	-	-	0.328	0.290	0.363	-0.07.
8	0.045	0.043	0.046	-0.003	-	-	-	-	0.330	0.277	0.388	-0.011*
9	0.024	0.032	0.017	0.015	-	-	-	-	0.251	0.216	0.2887	-0.071
10	0.044	0.027	0.061	-0.034	0.242	0.153	0.335	-0.182*	0.210	0.169	0.254	-0.085*
11	0.032	0.017	0.049	-0.032*	0.186	0.105	0.282	-0.177*	0.173	0.134	0.213	-0.079
12	0.039	0.030	0.038	-0.008	0.214	0.118	0.330	-0.212*	0.219	0.179	0.271	-0.092*
13	0.053	0.033	0.073	-0.040*	0.246	0.123	0.359	-0.236*	0.215	0.145	0.302	-0.157*
14	0.056	0.042	0.070	-0.028	0.239	0.112	0.361	-0.249*	0.188	0.181	0.196	-0.015
15	0.082	0.047	0.116	0.031*	0.274	0.152	0.407	-0.255*	0.226	0.149	0.305	-0.156*
16	0.130	0.079	0.178	-0.108	0.277	0.086	0.465	-0.379*	0.232	0.209	0.256	-0.047
17	0.250	0.151	0.342	-0.191*	0.287	0.158	0.464	-0.306*	0.287	0.218	0.375	-0.157*

Note: * denotes that the gender difference is statistically significant at 5% significance level.

Table 2E: Hotelling T^2-Statistics (Testing for Equality between Vector of Means of Boys and Girls)

Age	Peru	Pakistan	Ghana
6	2.74	-	0.03
7	2.13	-	7.15
8	4.33	-	8.64
9	2.41	-	3.65
10	7.14	78.43*	5.22
11	9.69*	68.43*	5.27
12	7.73	88.22*	1.48
13	10.74*	78.50*	18.34*
14	13.21*	95.31*	14.24*
15	18.88*	72.51*	24.56*
16	15.65*	178.93*	6.11
17	53.76*	81.47*	14.36*
Overall	86.35*	643.27*	66.47*

Note: * denotes statistical significance at 5% significance level.

Table 3: Percentage Share of Income from Child Labour

	All	Boys	Girls
Peru			
Only Work	9.77	14.11	4.77
Both Work & School	3.58	3.79	3.26
Pakistan			
Only Work	23.37	30.33	16.05
Both Work & School	10.18	8.56	10.57
Ghana			
Only Work	30.14	30.33	31.22
Both Work & School	19.87	25.77	13.96

Table 4: Multinomial Logit Estimates for Category[a]: School Only

Variable	Peru		Pakistan		Ghana	
	Coefficient Estimate[b]	Relative Risk Ratio	Coefficient Estimate[b]	Relative Risk Ratio	Coefficient Estimate[b]	Relative Risk Ratio
AGE	-0.432[c] (0.097)	0.649	-0.692[c] (0.350)	0.501	-1.052[c] (.129)	.349
AGE2	0.007 (0.004)	1.007	0.018 (0.013)	1.018	0.032[c] (0.005)	1.033
GIRL	0.745[c] (0.083)	2.107	0.910[c] (0.135)	2.485	0.240[c] (0.100)	1.272
URBAN	1.782[c] (0.128)	5.944	1.123[c] (0.292)	3.075	0.116 (0.147)	1.123
NCHILD	-0.051 (0.026)	0.951	-0.015 (0.021)	0.985	-0.043[c] (0.022)	0.958
NADULT	0.106[c] (0.038)	1.112	0.081[c] (0.029)	1.085	0.032 (0.041)	1.033
AMOUNTL	-	-	-0.000[c] (0.000)	1.000	-0.000[c] (0.000)	1.000
AMOUNTB	-	-	-0.000 (0.000)	1.000	0.000[c] (0.000)	1.000
FHH	0.030 (0.170)	1.031	-0.411 (0.377)	0.663	0.337[c] (0.112)	1.400
HEADAGE	-0.001 (0.004)	0.999	0.000 (0.005)	1.00	-0.006 (0.004)	0.994
LANGHH	-	-	0.149 (0.170)	1.161	-0.431[c] (0.120)	0.650
MAXFEMED	0.037[c] (0.011)	1.037	0.070[c] (0.018)	1.072	0.007 (0.011)	1.007
WATER 1	-	-	0.353[c] (0.135)	1.423	-	-
ROAD	-	-	0.209 (0.125)	1.232	-	-
CLOSEDDR	-	-	0.244 (0.184)	1.277	-	-
DISPOS1	-	-	0.037 (0.177)	1.037	-	-
DWATER	-	-	-	-	-0.483[c] (0.111)	0.617
TOILET	-	-	-	-	-0.509[c] (0.111)	0.601
LIGHT	-	-	-	-	-0.470[c] (0.155)	0.625

Table 4: Continued

Variable	Peru		Pakistan		Ghana	
	Coefficient Estimate[b]	Relative Risk Ratio	Coefficient Estimate[b]	Relative Risk Ratio	Coefficient Estimate[b]	Relative Risk Ratio
ELECTR	0.354[c] (0.122)	1.425	-	-	-	-
WATER2	-0.382[c] (0.108)	0.682	-	-	-	-
WATERC	-0.094 (0.083)	0.911	-	-	-	-
DISPOS2	0.303[c] (0.143)	1.354	-	-	-	-
BOYSC	-	-	0.010 (0.033)	1.010	-	-
GIRLSC	-	-	-0.104[c] (0.049)	0.902	-	-
COEDSC	-	-	0.015 (0.051)	1.016	-	-
BOYCLOS	-	-	0.025 (0.268)	0.975	-	-
GIRLCLOS	-	-	-0.142 (0.241)	1.152	-	-
COEDCLOS	-	-	-0.136 (0.166)	1.146	-	-
PRIMYES	-	-	-	-	-0.022 (0.111)	0.978
POV	-0.048 (0.110)	0.953	0.256 (0.215)	1.292	-0.523[c] (0.185)	0.593
PCEX	0.000[c] (0.000)	1.000	0.000 (0.000)	1.000	0.000 (0.000)	1.000
MAXMWAGE	0.040 (0.025)	1.041	0.000 (0.004)	1.000	0.000 (0.000)	1.000
MAXFWAGE	-0.008 (0.032)	0.992	-0.103[c] (0.016)	0.902	0.000 (0.000)	1.000
MAXFWAGE2	0.000 (0.000)	1.000	0.001 (0.000)	1.001	0.000 (0.000)	1.000

Note: [a] The normalised category is: both school and work.
[b] (Heteroskedasticity consistent) standard errors in brackets.
[c] Denotes significance at 5% significance level.

Table 5: Multinomial Logit Estimates for Category[a]: Work Only

Variable	Peru		Pakistan		Ghana	
	Coefficient Estimate[b]	Relative Risk Ratio	Coefficient Estimate[b]	Relative Risk Ratio	Coefficient Estimate[b]	Relative Risk Ratio
AGE	-0.805[c] (0.225)	0.447	-0.464 (0.373)	0.629	-0.433[c] (.176)	0.649
AGE2	0.043[c] (0.009)	1.044	0.024 (0.014)	1.025	0.025[c] (0.007)	1.025
GIRL	0.128 (0.152)	1.137	1.547[c] (0.138)	4.699	0.828[c] (0.125)	2.289
URBAN	1.727[c] (0.255)	2.069	0.405 (0.302)	1.500	-0.589[c] (0.202)	0.555
NCHILD	-0.036 (0.049)	0.965	0.011 (0.022)	1.011	-0.038 (0.026)	0.962
NADULT	0.106 (0.058)	1.111	-0.075[c] (0.033)	0.928	0.118[c] (0.048)	1.125
AMOUNTL	-	-	-0.000 (0.000)	1.000	-0.000 (0.000)	1.000
AMOUNTB	-	-	-0.000 (0.000)	1.000	0.000 (0.000)	1.000
FHH	0.554[c] (0.282)	1.740	-0.259 (0.406)	0.772	-0.360[c] (0.152)	0.698
HEADAGE	0.010 (0.008)	1.010	0.006 (0.005)	1.006	-0.004 (0.005)	0.996
LANGHH	-	-	-0.141 (0.182)	0.869	-0.535[c] (0.171)	0.585
MAXFEMED	-0.070[c] (0.021)	0.932	-0.081[c] (0.022)	0.922	-0.206[c] (0.017)	0.814
WATER1	-	-	-0.136 (0.147)	0.873	-	-
ROAD	-	-	-0.136 (0.134)	0.873	-	-
CLOSEDDR	-	-	-0.038 (0.203)	0.963	-	-
DISPOS1	-	-	0.224 (0.193)	1.251	-	-
DWATER	-	-	-	-	-0.615[c] (0.138)	0.541
TOILET	-	-	-	-	-0.963[c] (0.135)	0.382
LIGHT	-	-	-	-	-0.028 (0.210)	0.973

Table 5: Continued

Variable	Peru		Pakistan		Ghana	
	Coefficient Estimate[b]	Relative Risk Ratio	Coefficient Estimate[b]	Relative Risk Ratio	Coefficient Estimate[b]	Relative Risk Ratio
ELECTR	-0.947[c] (0.245)	0.388	-	-	-	-
WATER2	-0.602[c] (0.211)	0.548	-	-	-	-
WATERC	-0.105 (0.153)	0.901	-	-	-	-
DISPOS2	0.110 (0.310)	1.116	-	-	-	-
BOYSC	-	-	0.009 (0.034)	1.009	-	-
GIRLSC	-	-	-0.183[c] (0.058)	0.833	-	-
COEDSC	-	-	0.112[c] (0.049)	1.118	-	-
BOYCLOS	-	-	-0.011 (0.268)	1.011	-	-
GIRLCLOS	-	-	-0.298 (0.239)	1.347	-	-
COEDCLOS	-	-	0.081 (0.170)	0.922	-	-
PRIMYES	-	-	-	-	-0.035 (0.136)	0.966
POV	0.154 (0.195)	1.166	0.743[c] (0.225)	2.102	0.331 (0.198)	1.393
PCEX	0.000 (0.000)	1.000	-0.000[c] (0.000)	1.000	0.000 (0.000)	1.000
MAXMWAGE	-0.038 (0.050)	0.963	-0.014[c] (0.005)	0.986	0.000 (0.000)	1.000
MAXFWAGE	-0.061 (0.070)	0.941	-0.033[c] (0.016)	0.967	-0.000 (0.000)	1.000
MAXFWAGE2	0.001 (0.001)	1.001	0.001[c] (0.000)	1.001	0.000 (0.000)	1.000

Note: [a] The normalised category is: both school and work.
[b] (Heteroskedasticity consistent) standard errors in brackets.
[c] Denotes significance at 5% significance level.

Table 6: Multinomial Logit Estimates for Category[a]: Neither in School nor in Work

Variable	Peru		Pakistan		Ghana	
	Coefficient Estimate[b]	Relative Risk Ratio	Coefficient Estimate[b]	Relative Risk Ratio	Coefficient Estimate[b]	Relative Risk Ratio
AGE	-1.745[c] (0.143)	0.175	-1.232[c] (0.374)	0.292	-1.891[c] (.136)	0.151
AGE2	0.072[c] (0.006)	1.075	0.047[c] (0.014)	1.048	0.072[c] (0.006)	1.074
GIRL	1.106[c] (0.030)	3.023	2.566[c] (0.142)	13.012	0.918[c] (0.109)	2.505
URBAN	1.344[c] (0.198)	3.835	0.290 (0.302)	1.337	-0.009 (0.159)	0.992
NCHILD	0.020 (0.040)	1.020	0.012 (0.022)	1.012	-0.038 (0.023)	0.963
NADULT	0.151[c] (0.051)	1.163	0.020 (0.032)	1.020	0.136[c] (0.044)	1.146
AMOUNTL	-	-	-0.000[c] (0.000)	1.000	-0.000 (0.000)	1.000
AMOUNTB	-	-	-0.000[c] (0.000)	1.000	0.000[c] (0.000)	1.000
FHH	-0.051 (0.246)	0.950	-0.257 (0.412)	0.774	0.193 (0.126)	1.213
HEADAGE	0.014[c] (0.007)	1.014	0.005 (0.005)	1.005	-0.008 (0.004)	0.992
LANGHH	-	-	-0.353 (0.182)	0.702	-0.448[c] (0.135)	0.639
MAXFEMED	0.025[c] (0.017)	1.026	0.027 (0.020)	0.973	-0.177[c] (0.014)	0.838
WATER1	-	-	0.218 (0.150)	1.243	-	-
ROAD	-	-	0.056 (0.135)	1.057	-	-
CLOSEDDR	-	-	-0.184 (0.199)	0.832	-	-
DISPOS1	-	-	0.125 (0.191)	1.133	-	-
DWATER	-	-	-	-	-0.668[c] (0.120)	0.513
TOILET	-	-	-	-	-0.768[c] (0.119)	0.464
LIGHT	-	-	-	-	-0.150 (0.171)	0.861

Table 6: Continued

Variable	Peru		Pakistan		Ghana	
	Coefficient Estimate[b]	Relative Risk Ratio	Coefficient Estimate[b]	Relative Risk Ratio	Coefficient Estimate[b]	Relative Risk Ratio
ELECTR	0.008 (0.191)	1.008	-	-	-	-
WATER2	-0.563[c] (0.174)	0.569	-	-	-	-
WATERC	0.138 (0.130)	1.148	-	-	-	-
DISPOS2	0.116 (0.214)	1.123	-	-	-	-
BOYSC	-	-	-0.012 (0.035)	0.988	-	-
GIRLSC	-	-	-0.306[c] (0.065)	0.736	-	-
COEDSC	-	-	-0.057 (0.053)	0.945	-	-
BOYCLOS	-	-	-0.260 (0.273)	1.297	-	-
GIRLCLOS	-	-	-0.543[c] (0.245)	1.721	-	-
COEDCLOS	-	-	0.050 (0.182)	0.951	-	-
PRIMYES	-	-	-	-	-0.364[c] (0.121)	0.695
POV	0.461[c] (0.170)	1.586	0.818[c] (0.229)	2.267	0.038 (0.187)	1.038
PCEX	0.000[c] (0.000)	1.000	0.000 (0.000)	1.000	0.000 (0.000)	1.000
MAXMWAGE	0.033 (0.030)	1.034	-0.012[c] (0.004)	0.988	-0.000[c] (0.000)	1.000
MAXFWAGE	-0.022 (0.050)	1.023	-0.102[c] (0.017)	0.903	0.000[c] (0.000)	1.000
MAXFWAGE2	-0.001 (0.002)	0.999	0.002[c] (0.000)	1.002	0.000 (0.000)	1.000

Note: [a] The normalised category is: both school and work.
[b] (Heteroskedasticity consistent) standard errors in brackets.
[c] Denotes significance at 5% significance level.

Table 7: Multinomial Logit Marginal Probabilities for a Selection of Variables

Variable	Peru				Pakistan				Ghana			
	School Only	Both School & Work	Neither School Nor Work	Work Only	School Only	Both School & Work	Neither School Nor Work	Work Only	School Only	Both School & Work	Neither School Nor Work	Work Only
AGE	0.0212	0.0735	-0.0887	-0.0060	0.0275	0.0412	-0.1173	0.0486	0.0518	0.1137	-0.2168	0.0513
GIRL	0.0797	-0.1029	0.0321	-0.0089	-0.2363	-0.0754	0.2858	0.0259	-0.1159	-0.0449	0.1344	0.0264
URBAN	0.2733	-0.2587	-0.0028	-0.0118	0.2029	-0.0412	-0.1055	-0.0562	0.0493	-0.0026	-0.0102	-0.0364
NCHILD	-0.0100	0.0060	0.0040	0.0000	-0.0061	0.0002	0.0035	0.0024	-0.0033	0.0037	-0.0003	-0.0001
NADULT	0.0105	-0.0148	0.0041	0.0002	0.0246	-0.0019	-0.0036	-0.0190	-0.0178	-0.0065	0.0206	0.0037
FHH	-0.0007	-0.0050	-0.0055	0.0112	-0.0468	0.0207	0.0154	0.0107	0.0652	-0.0206	-0.0071	-0.0375
HEADAGE	-0.0010	-0.0001	0.0009	0.0002	-0.0012	-0.0001	0.0007	0.0006	-0.0002	0.0006	-0.0006	0.0001
MAXFEMED	0.0064	-0.0045	-0.0002	-0.0017	0.0283	-0.0009	-0.0104	-0.0169	0.0373	0.0062	-0.0333	-0.0103
POV	-0.0385	-0.0006	0.0364	0.0027	-0.1144	-0.0225	0.0890	0.0479	-0.1494	0.0224	0.0790	0.0481
Base Probability	0.7539	0.1596	0.0691	0.0174	0.5309	0.0554	0.2399	0.1738	0.5370	0.0990	0.2922	0.0717

Table 8: Ordered Logit Marginal Probabilities for a Selection of Variables

Variable	Peru				Pakistan				Ghana			
	School Only	**Both School & Work**	**Neither School Nor Work**	**Work Only**	**School Only**	**Both School & Work**	**Neither School Nor Work**	**Work Only**	**School Only**	**Both School & Work**	**Neither School Nor Work**	**Work Only**
AGE	-0.0810	-0.0535	-0.0179	-0.0095	0.0018	0.0000	-0.0008	-0.0009	0.0899	-0.0042	-0.0550	-0.0307
GIRL	0.0489	-0.0323	-0.0109	-0.0058	-0.1927	0.0034	0.0853	0.1040	-0.1108	0.0049	0.0676	0.0384
URBAN	0.2256	-0.1424	-0.0536	-0.0296	0.0942	-0.0018	-0.0425	-0.0498	0.0665	-0.0048	-0.0406	-0.0210
NCHILD	-0.0084	0.0056	0.0019	0.0010	-0.0062	0.0001	0.0028	0.0032	-0.0009	0.0000	0.0006	0.0003
NADULT	0.0013	-0.0009	-0.0003	-0.0002	0.0208	-0.0004	-0.0095	-0.0109	-0.0183	0.0009	0.0112	0.0063
FHH	-0.0235	0.0154	0.0053	0.0028	-0.0352	0.0003	0.0155	0.0194	0.0860	-0.0056	-0.0526	-0.0278
HEADAGE	-0.0012	0.0008	0.0003	0.0001	-0.0011	0.0000	0.0005	0.0006	-0.0002	0.0000	0.0001	0.0001
MAXFEMED	0.0085	-0.0056	-0.0019	-0.0010	0.0292	-0.0006	-0.0133	-0.0153	0.0385	-0.0018	-0.0236	-0.0131
POV	-0.0461	0.0300	0.0105	0.0056	-0.1189	-0.0018	0.0480	0.0727	-0.1316	-0.0022	0.0787	0.0551
Base Probability	0.7112	0.2135	0.0506	0.0248	0.4832	0.0914	0.2706	0.1549	0.4612	0.1537	0.2917	0.0935

Table 9: Ordered Logit Coefficient Estimates on Combined Country Data

Variable	Coefficient Estimate[a]
AGE	-0.323[b] (0.039)
AGE2	0.022[b] (0.002)
GIRL	-0.193[b] (0.053)
URBAN	-0.801[b] (0.038)
NCHILD	0.026[b] (0.007)
NADULT	-0.042[b] (0.011)
FHH	-0.285[b] (0.051)
HEADAGE	0.004[b] (0.001)
MAXFEMED	-0.125[b] (0.004)
POV	0.259[b] (0.006)
Country Dummies	
D1 (1 = Pakistan, 0 = Peru, Ghana)	0.032 (0.063)
D2 (1 = Ghana, 0 = Peru, Pakistan)	0.501[b] (0.061)
Dummy Interactions	
D1*POV	0.366[b] (0.113)
D2*POV	0.484[b] (0.100)
D1*GIRL	1.097[b] (0.079)
D2*GIRL	0.615[b] (0.077)

[a] Standard errors in brackets
[b] Statistically significant at 5% level of significance.

Table 10: Ordered Logit Marginal Probabilities on Combined Country Data

Variable	Marginal Probabilities			
	School Only	**Both School & Work**	**Neither School nor Work**	**Work Only**
AGE	0.0800	-0.0147	-0.0399	-0.0254
GIRL	0.0478	-0.0088	-0.0238	-0.0152
URBAN	0.1946	-0.0372	-0.0962	-0.0612
NCHILD	-0.0064	0.0012	0.0032	0.0020
NADULT	0.0105	-0.0019	-0.0052	-0.0033
FHH	0.0696	-0.0146	-0.0344	-0.0206
HEADAGE	-0.0010	0.0002	0.0005	0.0003
MAXFEMED	0.0308	-0.0057	-0.0154	-0.0098
POV	-0.0643	0.0101	0.0323	0.0219
Country Dummies				
D1 (1 = Pakistan, 0 = Peru, Ghana)	-0.0078	0.0014	0.0039	0.0025
D2 (1 = Ghana, 0 = Peru, Pakistan)	-0.1242	0.0191	0.0623	0.0428
Dummy Interactions				
D1*POV	-0.0913	0.0122	0.0460	0.0331
D2*POV	-0.1204	0.0140	0.0606	0.0458
D1*GIRL	-0.2662	0.0185	0.1309	0.1168
D2*GIRL	-0.1526	0.0179	0.0767	0.0580
Base Probability	0.5516	0.1677	0.1948	0.0858

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Appendix
Table A1: Ordered[a] Logit Estimates[b] by Country

Variable	**Peru**	**Pakistan**	**Ghana**
AGE	-0.394[c] (0.074)	-0.007 (0.156)	-0.362[c] (0.064)
AGE2	0.028[c] (0.003)	0.010 (0.006)	0.023[c] (0.003)
GIRL	-0.238[c] (0.064)	0.782[c] (0.055)	0.448[c] (0.057)
URBAN	-1.069[c] (0.104)	-0.378[c] (0.131)	-0.267[c] (0.085)
NCHILD	0.041[c] (0.020)	0.025[c] (0.010)	0.004 (0.012)
NADULT	-0.006 (0.027)	-0.083[c] (0.015)	0.074[c] (0.023)
AMOUNTL	-	0.000 (0.000)	0.000 (0.000)
AMOUNTB	-	0.000 (0.000)	0.000 (0.000)
FHH	0.112 (0.137)	0.141 (0.188)	-0.346[c] (0.069)
HEADAGE	0.006[c] (0.003)	0.005[c] (0.002)	0.001 (0.002)
LANGHH	-	-0.268[c] (0.081)	-0.027 (0.077)
MAXFEMED	-0.041[c] (0.009)	-0.117[c] (0.009)	-0.155[c] (0.007)
WATER1	-	-0.319[c] (0.065)	-
ROAD	-	-0.224[c] (0.059)	-
CLOSEDDR	-	-0.306[c] (0.081)	-
DISPOS1	-	0.140 (0.080)	-
DWATER	-	-	-0.111[c] (0.064)
TOILET	-	-	-0.300[c] (0.062)
LIGHT	-	-	0.352[c] (0.092)
ELECTR	-0.488[c] (0.096)	-	-
WATER2	0.062 (0.081)	-	-
WATERC	0.087 (0.065)	-	-

Table A1: Continued

Variable	Peru	Pakistan	Ghana
DISPOS2	-0.302[c] (0.115)	-	-
BOYSC	-	-0.001 (0.017)	-
GIRLSC	-	-0.068[c] (0.035)	-
COEDSC	-	0.081[c] (0.025)	-
BOYCLOS	-	-0.003 (0.121)	-
GIRLCLOS	-	-0.093 (0.104)	-
COEDCLOS	-	0.148 (0.086)	-
PRIMYES	-	-	-0.088 (0.064)
POV	0.219[c] (0.080)	0.486[c] (0.092)	0.547[c] (0.094)
PCEX	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
MAXMWAGE	-0.018 (0.015)	-0.011[c] (0.002)	0.000 (0.000)
MAXFWAGE	0.008 (0.024)	0.040[c] (0.008)	0.000 (0.000)
MAXFWAG2	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Thresholds			
μ_1	-0.590 (0.432)	0.952 (1.039)	-1.456 (0.368)
μ_2	1.016 (0.440)	1.320 (1.039)	-0.833 (0.369)
μ_3	2.181 (0.434)	2.717 (1.038)	0.972 (0.360)

Notes:
[a] Categories ordered in terms of child welfare.
[b] (Heteroskedasticity consistent) Standard errors in brackets.
[c] Denotes significance at 5% significant level.