Theoretical and Applied Economics
Volume XXVI (2019), No. 2(619), Summer, pp. 261-276

What discriminates the welfare outcomes of children in India. A multiple discriminant analysis in selected states

Atul MEHTA
Indian Institute of Management Shillong, Meghalaya, India
f11atulm@iimidr.ac.in
Joysankar BHATTACHARYA
Indian Institute of Management Indore, India
joysankar@iimidr.ac.in

Abstract. *This paper aims to look at the factors that play an important role in discriminating welfare outcomes of children. The paper considers school participation and incidence of child labour as two important indicators of children welfare. The study has been carried out in four Indian states: Tamil Nadu and Himachal Pradesh as states with considerably better welfare outcomes and Bihar, Uttar Pradesh and Madhya Pradesh being the poor performing states. The unique feature of this paper is that it computes a child welfare index combining the schooling and labour outcomes of children using NFHS-3 survey data and employs Multiple Discriminant Analysis (MDA) technique to determine the household level factors that distinguish between the welfare outcome of children in terms of education and child labour. The results confirm that the incidence of child labour and poor school participation is not mutually exclusive and thus there are common factors that affect both the outcomes.*

Keywords: child labour, schooling, child welfare, discriminant analysis, NFHS.

JEL Classification: I21, I28, I31, J70.

1. Introduction

Children are considered as the key assets of a nation. Their welfare enhancement is widely recognised as the primary agenda of government policies in developing countries. The global estimates released by International Labour Organisation (ILO) shows the number of working children to be 168 million in 2012 (ILO-IPEC, 2013). More than half of them, 85 million, are engaged in hazardous work. Incidence of child labour is more prevalent in Asia and the Pacific region. In India, it is estimated that there are 4.4 million child labourers age 5-14 years (Census, 2011). Child labour covers a wide range of occupations from performing household chores to engagement in bonded labour in various industries.

Another component of children's welfare is education or the level of schooling. . Level of schooling and incidence of child labour together substantially contribute to the welfare outcomes of children. Investment in education in a country fetches high returns in the labour markets (Vijverberg, 1993; Glick and Sahn, 2000). Both self-employment and wage employment witness a higher earning with an increase in schooling (Glick and Sahn, 1997). Also, the returns of child education in labour markets are higher than other physical assets (Psacharopoulos, 1994). Despite the obvious advantages of child education, the incidence of schooling and level of child education remain abysmally low in most developing countries with high prevalence rate of child labour. A range of empirical studies support the dependence of economic growth on the quality and stock of human capital in a country (Lucas, 1988; Barro, 1991; Mankiw et al., 1992). Human capital development not only facilitates economic growth in a country but it also helps elimination of poverty.

Unavailability of a school in a particular region or the one of low quality also affects the schooling and work decision of households for their children. It induces parents to involve their children into more profitable activities. High cost of schooling could also be another determining factor responsible for work participation of children (Siddiqi and Patrinos, 1995). Because of poverty, households may also decide to engage their children into labour instead of school.

A family is looked upon as the primary informal institution responsible for children's welfare. Since family plays a key role in deciding the physical, mental, and social well being of a child, a variety of factors at household level play an important role in determining the labour and schooling outcomes of children. Poverty and nutritional deprivation of the households severely affects the welfare outcomes of children under 15 years of age. Such children are characterized with low schooling and high labour participation. The discrimination of children in a household in terms of lack of schooling and engagement into labour force is a complex phenomenon with a range of socio-economic factors at play. Children in poor families are most vulnerable to exploitation and abuse. Poor parents view their children as current economic resource instead of future economic resource. This result in their entry into the labour market at the time of childhood due to which they fail to develop the skills and competencies necessary to become productive adults.

In India very often public interventions begin until the children reach school-going age, when they are finally herded into school for education and attention. Yet the first six years of life have a decisive and lasting influence on a child's health, well-being, aptitudes and

opportunities. The long-standing neglect of childcare services in India arises partly from a common assumption that the care of young children is best left to the household. Parents are indeed best placed to look after their children, and generally to take care of them. But parents often lack resources, energy, power, and time to take adequate care of their children, even when commitment and knowledge of what has to be done are not lacking (Sen, 2013). What they can do for their children depends on various forms of social support, including health services, crèche facilities and maternity entitlements. Further many parents have limited knowledge of matters relating to childcare and nutrition.

A number of policy initiatives have been taken by Government of India to address the issue of children welfare. This includes a range of policies, legislations, and child rights to ensure the physical, mental, and social development of children at different growing stages of their life. The broad issues addressed are children's health, nutrition, education, and child labour. However, such policies are designed at national level and do not take into account the state-specific factors that affect the welfare outcomes of children due to which there is wide variation in the incidence of child labour as well as school drop-out rates. This results in a mismatch between the targeted and the actually responsible factors for discrimination of children at state level. As per Census 2011, the incidence of child labour as well as school drop-out rate at primary level is high in states such as Uttar Pradesh, Bihar and Madhya Pradesh whereas it is substantially lower in Tamil Nadu and Himachal Pradesh. State governments do act as implementing authorities and conduct inspections and raids to detect cases of child labour, but their role remains limited in designing of policies. Thus, appropriate policies to address the issue of child welfare require identification of state-specific factors that are responsible for the discrimination of welfare outcomes of children.

Multiple Discriminant Analysis (MDA) is a technique used to determine the factors that discriminate between two or more groups of the dependent variable. It also assesses the relative importance of each factor or independent variable in classifying the dependent variable. Applying MDA, this paper determines the household level factors that distinguish between the welfare outcomes of children in terms of education and child labour in states of Bihar, Himachal Pradesh, Madhya Pradesh, Tamil Nadu, and Uttar Pradesh. The states are selected based on their rankings in child labour participation and school drop-out rate across states. This paper makes a unique methodological contribution by combining the level of schooling and incidence of child labour to form a child welfare index to identify the factors that discriminate the welfare outcomes of children in the selected states. The specific research questions that the paper attempts to answer are:

- What is the difference in the household level socio-economic and demographic factors across the low, medium, and high category of child welfare?
- What is the difference in the household level socio-economic and demographic factors between low and high child welfare states?
- How much of the variation in child welfare is explained by various household level factors across states?
- What is the relative importance of the factors in classifying the welfare outcomes of children into low, high, and medium category in each state?

2. Methodology

After considering the nature of the research problem and the purpose of the paper, MDA was selected as the appropriate statistical technique. Since its very first application in the 1930's, MDA has been used by a range of disciplines. Taking into account the individual characteristics of an observation, MDA attempts to classify an observation into one of the a priori groups. The number of a priori groups can be two or more. After the groups are established, data on various characteristics of each observation in the groups is collected. Using this information, MDA derives a linear combination of chosen characteristics which best discriminates between the groups.

The primary objective of using MDA is to predict a group membership which starts with examining any significant differences between groups on mean value of each of the independent variables. The statistical significance of the mean values between groups is ascertained by 'F-test' of equality of group means.

One of the key assumptions in MDA is the equality of variance-covariance matrices between the groups of dependent variable. Box's M tests the null hypothesis that there is no significant difference in covariance matrices between the groups formed by dependent variable and the test is required to be insignificant so that the null hypothesis can be retained.

A discriminant function in MDA provides a discriminant score (L) which is a latent variable and is also a linear combination of independent variables of the form:

$$L = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots \ldots + \beta_i X_i + a \qquad (1)$$

Where:
L = latent variable;
β = discriminant coefficients;
X = discriminating variable;
a = constant;
i = number of independent variables.

Discriminant function is similar to a regression equation and discriminant coefficients can be interpreted as beta-weights in regression. The number of discriminant functions produced by MDA equals one less than the number of group in the dependent variable or the number of independents used in MDA, whichever is lesser. If there are three groups in the independent variable and hence two discriminant functions, then the first function discriminates between the first group and the second and third group combined. The second function discriminates between the second and the third group (excluding the first group). Thus, each discriminant function is orthogonal to other. The first function which covers all the three groups in the dependent variable is thus the largest and the most important one in terms of explanatory power followed by second one and so on. The contribution of each discriminant function to the explanatory power of all the functions combined or the model as a whole is nothing but the ratio of the Eigenvalues of each function to the sum of Eigenvalues of all functions together.

The usefulness of each discriminant function in determining the group differences is indicated by canonical correlation (R) which measures the correlation between the groups formed by the dependent variable and the discriminant scores. The value of R ranges from '0' to '1' where '0' indicates no relation and '1' indicates perfect association. When squared (R^2), R represents the percent of variation in the dependent discriminated by the set of independents. The statistical significance of the Eigenvalue associated with each discriminant function as a whole is tested by Wilk's Lambda statistic which ranges from '0' to '1'.

The unique contribution of each independent variable to the classification of cases into groups is reflected by the coefficients of standardized discriminant function. They are also termed as partial coefficients and are interpreted same as beta weights in multiple regression.

The final task is to classify individual cases into one of the groups of dependent variable which is the ultimate objective of MDA. The classification is done based on the discriminant scores obtained for each case. A mean discriminant score, which is called group centroid, is computed for each group of the dependent variable. Cases with discriminant score near to a centroid are classified as belonging to the respective group.

3. Data and variables

3.1. Data

Household level data of National Family Health Survey-3 (NFHS-3) for Bihar, Himachal Pradesh, Madhya Pradesh, Tamil Nadu, and Uttar Pradesh states has been used in the present study. The key feature of this survey is that it provides estimates of population, health, and nutrition indicators by background characteristics at the national and state levels. A brief overview of the list of variables used and sample size is provided in Table 1.

Table 1. *List of variables and descriptive statistics*

	Bihar		Himachal Pradesh		Madhya Pradesh		Tamil Nadu		Uttar Pradesh	
	Mean (N)	SD	Mean (N)	SD	Mean (N)	SD	Mean (N)	SD	Mean (N)	SD
Child Welfare Categories	1.44 (2364)	.69	2.43 (1684)	.72	1.79 (3780)	.80	2.36 (3199)	.73	1.58 (7739)	.75
Female Headship	0.22 (3016)	.42	0.18 (2790)	.38	0.08 (5488)	.27	0.19 (6344)	.39	0.13 (10026)	.34
SC/ST	0.17 (3016)	.37	0.22 (2790)	.42	0.34 (5488)	.47	0.25 (6344)	.43	0.24 (10026)	.43
Wealth level	2.75 (3016)	1.42	4.09 (2790)	1.01	3.05 (5488)	1.58	3.36 (6344)	1.26	3.0 (10026)	1.48
Location	0.61 (3016)	.49	0.66 (2790)	.47	0.49 (5488)	.50	0.49 (6344)	.50	0.58 (10026)	.49
HH Age	45.89 (3016)	14.5	48.54 (2789)	15.0	44.59 (5488)	14.3	46.81 (6344)	14.3	45.79 (10026)	14.3
HH education	4.81 (3014)	5.50	7.36 (2785)	5.26	6.15 (5488)	5.60	6.02 (6344)	4.99	5.58 (10000)	5.60
Dependency Ratio	1.08 (3016)	.99	0.63 (2790)	.70	0.78 (5488)	.72	0.61 (6344)	.65	1.02 (10026)	.90

Note: BH = Bihar, HP = Himachal Pradesh, MP = Madhya Pradesh, TN = Tamil Nadu, UP = Uttar Pradesh.

3.2. Variables

3.2.1. Dependent Variable – Child Welfare Index

The decision of parents to enrol their child for school is also the decision to not send their child for work. The factors that affect the education outcome of child are often the same that affect her involvement into labour. Child labour and lack of education coexist as a result of endemic poverty (Karabegovic and Clemens, 2005). Poverty level of the household remains at the core of child labour, though not the sole determinant of the problem. Other factors include education level of household head, and household size (Lopez-Calva, 2001). Uneducated parents fail to realize the benefits of educating their children and hence get them into some kind of work. Families who send at least one of their children to school are more than twice as likely to send their other children as well, irrespective of the financial status of their household.

Having identified the child labour and level of schooling as the two key components of children welfare, I compute child welfare index for each household combining information on the years of completed education by the children and incidence of child labour. The starting point is the computation of an education index for children in 5-18 years age-group. Assuming that a child enters a school latest by the age of 5, a new variable is computed reducing the age of each child by 5. The resulting number would be the years of education a child ought to have at his/her respective age. In order to compare this number with the actual years of education attained, a new variable is computed which is actual years of completed education as a percentage of the number computed in the last stage. This new variable also captures the effect of late enrolment of a child as well as early dropout from the school. Since this new variable is computed for each child in the household, an average of the percentage is computed to arrive at the performance of household in terms of their children's education. This average value is converted into a unit-free index following the computation of Human Development Index (HDI) methodology which is as follows:

$$x - index = \frac{xi - \min(x)}{\max(x) - \min(x)} \quad (2)$$

Next step is to compute the incidence of child labour in the household which is defined as the labour force participation of any children age 5-14 years in a household. Apart from involvement in hazardous forms of labour, the incidence of a child engaging in domestic tasks such as taking care of other dependents, household chore, and assisting in family business is also taken into account while measuring the incidence of child labour in a household. Such tasks may not be hazardous for children's health, but they do may result in permanent loss of their education (Beegle et al., 2008). Since child labour is a negative indicator of welfare, the incidence of child labour is computed as '0', '1' otherwise (no children involved in child labour).

Last step is to compute the sum of education index and incidence of child labour and convert the final value into an index using the same HDI methodology as before. This final index is termed as 'Child Welfare Index' and categorised into three equal categories of 0.33 each, namely, low, medium, and high and entered as dependent variable in the analysis.

3.2.2. Continuous independent variables

Based on the literature review conducted in the previous section, the paper includes seven independent variables in order to classify the cases into the three categories of the dependent variable, child welfare index. Out of seven, three are continuous variables, three are dummy and one is ordinal variable.

Dependency ratio

Dependents include population aged 0-14 and that aged 65+ in the household. Any increase in the number of dependents in the household reduces its full income (an income-dilution effect). The probability of child labour rises whereas that of schooling lowers with an increase in the number of dependents in a household. The number of children under 6 increases the probability of child labour for older children. Using binary Probit models, Ray (2000) confirms a positive effect of number of siblings on probability of work. Similarly, Emerson and Souza (2008) find a positive association between number of children and probability of child labour while a negative association with school participation.

We compute 'dependency ratio' defined as the ratio of the population aged 0-14 and that aged 65+ to the population aged 15-64 for each household. The members aged 15-64 are the working members of the household.

Education of the household head

Parental education has a positive association with child schooling and decision for working as child labour for boys in urban areas (Das and Mukherjee, 2007). Similar results were obtained in a subsequent study for both boys and girls in urban areas (Mukherjee and Das, 2008). Mother's education has a greater negative effect on child labour than father's education. A study in rural India suggests that mothers with less than primary education are more likely to involve their children into full-time work compared to full-time study and mothers with completed middle school are less likely to combine work and school for their children with no significant effect of father's education (Cigno and Rosati, 2000). Similarly, in Bangladesh, negative effects of mother's as well as father's education have been observed (Ravallion and Wodon, 1999). The probability of child neither in work nor in school is also determined by mother's education significantly with no effect of father's education. Such results hold not only for boys but also for a girl child (Emerson and Souza, 2008).

We consider years of completed education of the household head as another independent variable. This is straight away taken from the NFHS dataset without any modifications as no missing value or responses recorded as 'Don't know' were found.

Age of the household head

The stage of the household's lifecycle stage is indicated by the age of the household head. A child living with his/her grandparents witnesses different welfare outcomes than those living with their parents. In the absence of full controls for composition of household, the

age of the household head can be a significant determinant of the welfare outcomes of the children (Cardoso and Souza, 2004; Ersado, 2005; Emerson and Souza, 2008).

In our paper, the age of the member reported as household head is taken from NFHS data and used in the analysis. None of the household reported as 'Don't know' nor any missing values were found in the age column of the dataset.

3.2.3. Dummy independent variables

Three categorical variables namely, gender, caste, religion of the household head, and wealth status of the household were converted into dummy and introduced in the analysis. The missing responses, if any, were kept unchanged. A brief description of the dummy variables is given below.

Gender of the household head

There is a great variation in the proportion of female-headed households across regions with the greatest share prevalent in Africa. Households with female head witness greater allocation of investment in the future (Rubalcava et al., 2009) in terms of schooling compared to male headed households (Cardosa and Souza, 2004). The alternate proposition of higher incidence of child labour and lower incidence of schooling among female-headed households is supported by Grootaert (1999). A significant positive association between female headship and child labour participation was found by Bhalotra and Heady (2003) with no effect on schooling. Similar results are also reported by Amin et al., 2004. Another study conducted in Nepal, Peru, and Zimbabwe witnesses no effect of female headship on child labour participation or schooling (Ersado, 2005). However, when divided sample into rural and urban areas, female headship was found to have a negative effect on child labour and schooling in urban Zimbabwe and also a negative effect on schooling in rural Nepal.

The schooling outcome of girls in a female headed household is better than that of boys with no effect on child labour participation (Ray, 2000). Such a finding is the result of the altruism nature of mother being biased towards a girl child (Duflo, 2003).

The NFHS data reports the relationship to the head of the household as 'self' for members who are household head. Such responses were identified from the dataset and their corresponding gender was recorded in a new variable for each household to arrive at the gender of the household head. Since our analysis doesn't allow for categorical independent variables, we use the dummy form of it with female headship recoded as '1', '0' otherwise.

Caste of the household head

The division of Indian society based on caste also significantly affects the schooling outcomes of children. Households belonging to lower castes rarely complete the primary level of their children's education (Kabeer et al., 2003). Moreover, the dropped-out children from Dalit and Adivasi community get involved in child labour to a greater extent than average. Moreover, socio-economic status such as household income and minority status affects the involvement of parents in school activities of their children with low levels of involvement in case of low income and minority households (Calabrese, 1990).

Caste of the household head was originally divided into four categories, namely, Scheduled Caste (SC), Scheduled Tribe (ST), Other Backward Caste (OBC), and none of the above. The two categories of our interest are SC and ST which are recoded as '1' in the newly computed dummy variable, '0' otherwise.

Location of the household

The incidence of child labour is higher in rural areas compared to urban areas. After controlling for poverty in rural areas, a higher incidence of child labour in rural areas is a matter of concern. Poor school infrastructure and low rates of technical change also discourage school attendance in rural areas (Bhalotra and Tzannatos, 2003). Moreover, because of the informal nature of the rural economy and market imperfections, children may be easily hired for low skill jobs. The incidence of child labour and schooling changes significantly with a change in the location of the household from urban to rural or vice-versa.

Based on location of the household, the total sample is divided into two broad categories, namely, rural and urban. As suggested by literature, the incidence of child labour as well as a low school enrolment and high dropout rate is more prevalent in rural areas than urban areas, a new dummy variable for location is computed with rural recoded as '1', '0' otherwise.

3.2.4. Ordinal variable – Wealth status of the household

The obvious link between poverty and child labour can be understood with the Luxury Axiom by Basu and Van (1998) which says that a family will send a child to work only if the family's non-child labour income drops below some threshold. However, there are numerous studies providing a mixed evidence for a linkage between the two. Studies that found an insignificant link between poverty and child labour include Ilahi (2001), Ray (2000), and Ersado (2005). Similar conclusion was derived by Bhatty (1998) for India. Contrary to that, absence of well functioning labour market results in a positive association between household wealth/income and child labour. A number of studies confirm that farm/enterprise owners do not involve their children into labour but they do hire their own family members including children to run their own business (Bhalotra and Heady, 2003; Dumas, 2007). Another group of studies in different countries confirm a negative association between household income and incidence of child labour. The studies cover rural as well as urban boys and girls involved in child labour (Cigno and Rosati, 2000; Amin et al., 2004; Liu, 1998; Ray, 2000). Studies with cash transfers such as pension as a source of income also confirm a negative association with child labour (Carvalho, 2000; Edmonds, 2006; Schady and Araujo, 2006).

Poverty not only affects incidence of child labour but it also affects schooling of the children with varying effects. Again, there is a mix of evidence of the effect of income on schooling across countries. A significant positive effect of income on school enrolment of boys and girls in rural as well as urban areas is confirmed by several studies conducted in different countries (Ray, 2000; Cigno et al., 2001; Ilahi, 2001; Canagarajah and Coulombe, 1999; Grootaert, 1999). Studies also confirm a positive non-linear relationship between income and schooling of children (Rosati and Tzannatos, 2006) and a positive effect of conditional (Schady and Araujo, 2006; Bourguignon et al., 2002; Cardoso and Souza,

2004) as well as unconditional cash transfers (Edmonds, 2006) on schooling. Studies with no significant effect of income on schooling include Ray (2000), Ilahi (2001), Ersado (2005). Another study conducted on rich households with large farms in Ghana and Pakistan finds coexistence of higher incidence of child labour with high school attendance (Bhalotra and Heady, 2003).

Based on 33 indicators of asset ownership and housing characteristics, a single wealth index is computed by NFHS. Based on the index value, the total population is divided into five equal groups of 20 percent each. The groups are numbered from 1 (lowest or poorest) to 5 (highest or richest). The ordinal variable thus computed by NFHS is entered as another independent variable in our analysis.

4. Results and discussions

With few exceptions, households with higher child welfare outcomes are found to have higher incidence of female headship, lower membership to SC/ST group, higher wealth and educated head, reside in urban areas, and have low dependency ratio across states (Table 2). It is interesting to note that the mean value of independents in high performing states (Tamil Nadu and Himachal Pradesh) is higher for female headship, wealth, education, whereas it is lower for membership to SC/ST, rural locality, and dependency ratio compared to poor performing states (Bihar, Madhya Pradesh, and Tamil Nadu). Such group difference in independents is statistically significant across states with few exceptions such as difference in female headship is not significant in Himachal Pradesh, Tamil Nadu, and Uttar Pradesh; and difference in the age of the household head is also not significant in Himachal Pradesh (Table 3).

Table 2. *Group statistics*

		Bihar		Himachal Pradesh		Madhya Pradesh		Tamil Nadu		Uttar Pradesh	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Low	Female Headship	.23	.42	.15	.36	.05	.21	.13	.34	.13	.33
	SC/ST	.18	.39	.32	.47	.43	.50	.36	.48	.25	.43
	Wealth level	2.43	1.29	3.52	1.13	2.38	1.43	3.07	1.23	2.61	1.37
	Location	.68	.47	.78	.42	.65	.48	.43	.50	.68	.47
	HH Age	44.55	12.96	47.65	15.14	42.36	11.88	40.79	10.44	44.09	12.83
	HH education	3.76	4.96	5.28	4.68	4.30	4.78	5.01	4.15	4.21	4.91
	Dependency Ratio	1.49	1.02	1.20	.86	1.23	.72	1.14	.65	1.43	.94
Medium	Female Headship	.18	.38	.18	.38	.07	.25	.14	.35	.13	.33
	SC/ST	.14	.35	.21	.41	.31	.46	.27	.44	.24	.43
	Wealth level	3.19	1.46	4.06	.99	3.28	1.54	3.28	1.20	3.19	1.48
	Location	.55	.50	.73	.44	.48	.50	.54	.50	.56	.50
	HH Age	46.85	14.7	47.87	14.5	43.43	13.2	41.79	10.6	44.58	13.2
	HH education	6.06	5.79	6.92	5.14	6.75	5.47	5.98	4.68	6.52	5.80
	Dependency Ratio	.86	.74	.95	.63	.92	.64	.99	.66	.97	.76

		Bihar		Himachal Pradesh		Madhya Pradesh		Tamil Nadu		Uttar Pradesh	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
High	Female Headship	.18	.38	.19	.40	.08	.27	.16	.37	.13	.34
	SC/ST	.11	.32	.23	.42	.28	.45	.24	.43	.21	.41
	Wealth level	3.85	1.30	4.18	.97	3.69	1.43	3.56	1.21	3.74	1.34
	Location	.39	.49	.65	.48	.35	.48	.48	.50	.44	.50
	HH Age	45.37	14.9	47.53	13.5	46.53	12.5	44.68	10.7	47.91	12.8
	HH education	8.33	5.40	7.64	5.08	7.54	5.71	6.64	4.93	7.87	5.87
	Dependency Ratio	.31	.53	.67	.71	.39	.53	.60	.62	.46	.60

Table 3. *Tests of equality of group means*

	Bihar		Himachal Pradesh		Madhya Pradesh		Tamil Nadu		Uttar Pradesh	
	F	Sig.	F	Sig.	F	Sig.	F	Sig.	F	Sig.
Female Headship	3.84	0.02	1.16	0.31	5.56	0.00	2.18	0.11	0.02	0.98
SC/ST	5.10	0.01	5.49	0.00	40.19	0.00	14.60	0.00	4.72	0.01
Wealth level	168.57	0.00	39.69	0.00	270.98	0.00	36.93	0.00	364.31	0.00
Location	51.46	0.00	9.79	0.00	122.42	0.00	9.27	0.00	133.60	0.00
HH Age	5.39	0.00	0.10	0.91	33.28	0.00	37.57	0.00	42.37	0.00
HH education	110.20	0.00	20.68	0.00	138.66	0.00	23.29	0.00	288.98	0.00
Dependency Ratio	239.55	0.00	63.74	0.00	478.60	0.00	191.76	0.00	682.99	0.00

The assumption of equality of variance-covariance matrices between the groups of dependent variable is found to have violated in our study (Table 4). The Box's test reveals a significant difference in covariance matrices between groups. However, studies with large samples do not regard a significant result as important. Thus, we may assume no significant difference between groups.

Table 4. *Box's test results*

State	Box's M	Sig.
Bihar	393.183	.000
Himachal Pradesh	113.718	.000
Madhya Pradesh	385.152	.000
Tamil Nadu	181.245	.000
Uttar Pradesh	698.643	.000

Tests null hypothesis of equal population covariance matrices.

With three groups in our dependent variable, the DA technique produces two discriminant functions (Table 5). The first function discriminates between low welfare group and not-low welfare group, i.e., medium and high welfare group combined. The second function discriminates between medium welfare group and high welfare group (excludes the low welfare group). Canonical correlation value for each state suggests that the first function is stronger in determining the group difference than the second one.

Table 5. *Eigenvalues*

	Bihar		Himachal Pradesh		Madhya Pradesh		Tamil Nadu		Uttar Pradesh	
Function	1	2	1	2	1	2	1	2	1	2
Eigenvalue	.324[a]	.003[a]	.125[a]	.013[a]	.350[a]	.020[a]	.172[a]	.013[a]	.271[a]	.003[a]
% of Variance	99.0	1.0	90.9	9.1	94.7	5.3	93.1	6.9	98.8	1.2
Cumulative %	99.0	100.0	90.9	100.0	94.7	100.0	93.1	100.0	98.8	100.0
Canonical Correlation	.494	.057	.333	.111	.509	.139	.384	.112	.462	.058

a. First 2 canonical discriminant functions were used in the analysis.

A statistically significant Wilk's Lambda in Table 6 confirms that the discriminant function as a whole is significant in predicting the group membership in all the 5 states except for second function in Bihar state.

Table 6. *Wilks' Lambda*

	Bihar		Himachal Pradesh		Madhya Pradesh		Tamil Nadu		Uttar Pradesh	
Test of Function(s)	1 through 2	2	1 through 2	2	1 through 2	2	1 through 2	2	1 through 2	2
Wilks' Lambda	.753	.997	.878	.988	.726	.981	.842	.987	.784	.997
Sig.	.000	.269	.000	.002	.000	.000	.000	.000	0.000	.000

Household wealth, female headship, and education level of the household head are the three contributors that positively discriminate the welfare outcomes of children between low and not-low group (first discriminant function) (Table 7). The contribution of female headship, indicated by its coefficient value, is highest in the two best performing states, i.e., Himachal Pradesh and Tamil Nadu. With a negative coefficient value, dependency ratio of the household emerges as the biggest discriminator of children welfare in all the five states. While rural location of the household has negative welfare effect in Bihar and Uttar Pradesh, such an effect is positive in Madhya Pradesh and Tamil Nadu. Similarly, presence of an older head deteriorates child welfare in Bihar whereas its effect is positive in the remaining states.

The changing sign of coefficients for female headship in the second discriminant function suggests that after a certain level of welfare, the female headship deteriorates the welfare outcome of children in the household. Such a pattern is observed in Bihar (with highest coefficient value), Himachal Pradesh, and Tamil Nadu. On the other hand, the positive effect of wealth increases significantly in the second function suggesting its sustaining impact on welfare outcomes with Bihar and Uttar Pradesh being exceptions where a decrease is witnessed. Older heads too have a negative effect after a certain level of welfare outcome is achieved.

Table 7. *Standardized canonical discriminant function coefficients*

	Bihar		Himachal Pradesh		Madhya Pradesh		Tamil Nadu		Uttar Pradesh	
	F1	F2	F1	F2	F1	F2	F1	F2	F1	F2
Female Headship	.262	-.386	.304	-.186	.136	.122	.302	-.044	.268	.071
SC/ST	.024	-.028	.022	-.411	-.035	-.124	-.113	-.331	.079	.145
Wealth level	.406	.308	.392	.866	.418	1.003	.288	.369	.285	-.043
Location	-.027	.386	-.016	.632	.059	.601	.280	.957	-.034	.114
HH Age	-.069	.804	.065	-.114	.084	-.249	.256	-.150	.119	-.667
HH education	.268	-.252	.310	-.132	.189	.223	.243	.302	.391	.657
Dependency Ratio	-.769	.038	-.779	.403	-.763	.534	-.825	.268	-.742	.181

Note: F1 = Function 1, F2 = Function 2.

The performance of DA technique in predicting group membership is presented in Table 8. For each state, the hit ratio is the percent of cases lying on the diagonal. These are the percentage of correctly classified cases for a particular group. The rows represent the observed categories whereas the columns represent the predicted categories. The entries in the diagonal of count section shows the number of cases correctly classified as low, medium, and high group and the diagonal in the percent section shows the percent of correctly classified cases.

The hit-ratio for the states as a whole stands highest for Bihar (58.6) followed by Madhya Pradesh (55.7), Uttar Pradesh (54.4), Himachal Pradesh (51.7), and Tamil Nadu (49.4). Among the three groups, the highest hit ratio is observed for high welfare group followed by low and medium welfare group. The probability of membership of each case to any one of the three groups of dependent variable is 0.3 which means the expected probability by chance is 33.3 percent. Comparing this with the overall hit-ratio of the states, we can say that the performance of DA in terms of its predictive accuracy is well above average.

Table 8. *Classification results*

	Bihar[a]			Himachal Pradesh[b]			Madhya Pradesh[c]			Tamil Nadu[d]			Uttar Pradesh[e]		
	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H
L	1040	368	195	133	41	56	1080	334	271	254	126	100	2799	939	730
M	150	151	183	148	167	189	396	338	460	396	306	400	713	506	809
H	22	60	193	212	165	568	102	113	686	293	304	1020	153	177	892
UC	167	219	266	171	119	815	378	170	1160	382	270	2493	548	429	1305
(%)															
L	64.9	23.0	12.2	57.8	17.8	24.3	64.1	19.8	16.1	52.9	26.3	20.8	62.6	21.0	16.3
M	31.0	31.2	37.8	29.4	33.1	37.5	33.2	28.3	38.5	35.9	27.8	36.3	35.2	25.0	39.9
H	8.0	21.8	70.2	22.4	17.5	60.1	11.3	12.5	76.1	18.1	18.8	63.1	12.5	14.5	73.0
UC	25.6	33.6	40.8	15.5	10.8	73.8	22.1	10.0	67.9	12.1	8.6	79.3	24.0	18.8	57.2

Note: L = Low, M = Medium, H = High, and UC = Ungrouped Cases.
a. 58.6% of selected original grouped cases correctly classified.
b. 51.7% of selected original grouped cases correctly classified.
c. 55.7% of selected original grouped cases correctly classified.
d. 49.4% of selected original grouped cases correctly classified.
e. 54.4% of selected original grouped cases correctly classified.

5. Conclusions and policy implications

We find a wide range of literature that explores the determinants of child labour and schooling in different countries. However, studies that examine the determinants of the two problems simultaneously are limited. This paper makes a unique contribution to the literature by combining the schooling outcomes and incidence of child labour to form a welfare index and to further identify the factors that discriminate the welfare outcomes of children in selected high and low child welfare states.

The incidence of child labour and poor school participation is not mutually exclusive and thus there are common factors that affect both the outcomes. Our broad conclusions are that female headship, wealth, and education level of the head positively affect the welfare outcomes of children whereas dependency ratio affects negatively in all the 5 states. Compared to low performing states (Bihar, Madhya Pradesh, and Uttar Pradesh), the incidence of female headship, educated head, and higher wealth is higher in high performing states (Himachal Pradesh and Tamil Nadu). Not just that, the positive contribution of female headship is highest in Himachal Pradesh and Tamil Nadu compared to other states. The deteriorating effects of rural location in Bihar and Uttar Pradesh and that of older heads in Bihar alone are also observed. Thus, while the number of negative factors is highest in Bihar, the contribution of factors affecting positively to the welfare of children is lowest in the state making it a poor performing state. The results also question the sustaining long-term effect of female headship and wealth in Bihar and Uttar Pradesh.

From policy implications perspective, a strict ban on child labour is not going to be an effective instrument and serve the purpose (Basu et al., 1997; Doepke and Zilibotti, 2009). There is a need to target the policy instruments that cause child labour resulting in low school enrolment. The state-specific household level factors that promote child labour and school drop-out needs to be taken into account. Since female headship improves welfare of children, welfare policies aimed at directly benefitting adult females in poor performing states should be framed. Similarly, in such states, policies should also focus on benefitting the households with greater number of dependents in rural areas. Considering the effect of wealth on child labour and education, conditional cash transfers could be one instrument as several developing countries have witnessed a great deal of improvement in school enrolment and decline in child labour after cash transfer schemes were implemented (Rawlings and Rubio, 2005; Maluccio and Flores, 2005; Handa and Davis, 2006). There is need of coordinated effort of various government departments to mitigate the problems of child labour and school drop-out. Families whose children are engaged in child labour needs to be provided with income generating opportunities through various development initiatives.

With respect to schooling outcomes of children, there is a need to formulate concrete strategies targeted to improve the functioning of labour markets especially in rural areas to prevent the children from engaging into work and improve their schooling outcomes. The access to quality education needs to be improved along with a mandatory school attendance. Since our study questions the sustainability of the positive effects of certain factors, the long-term policies aiming to eradicate child labour and discourage school drop-out need to be designed.

References

Amin, S., Quayes, M.S. and Rives, J.M., 2004. Poverty and Other Determinants of Child Labor in Bangladesh, *Southern Economic Journal,* June 70(4), pp. 876-892.

Barro, R., 1991. Economic growth in a cross section of countries. *Quarterly Journal of Economics* 106: 2 (May), 407-43.

Basu, Kaushik, and Pham Hoang Van., 1998. The Economics of Child Labor, *American Economic Review,* June 88(3): pp. 412-27.

Basu, K. and Zarghamee, H., 2009. Is product boycott a good idea for controlling child labor? A theoretical investigation. *Journal of Development Economics* 88(2), pp. 217-220.

Beegle, K., Gatti, R., Dehejia, R. and Krutikova, S., 2008. The Consequences of Child Labor: Evidence from Longitudinal Data in Rural Tanzania, Policy Research Working Paper 677, Washington DC: World Bank

Bhalotra, S. and Heady, C., 2003. Child Farm Labor: The Wealth Paradox. *The World Bank Economic Review,* 17(2), pp. 197-227.

Bhalotra, S. and Zafiris, T., 2003. Child Labor: What Have We Learnt? The World Bank Human Development Network. Social Protection Discussion Paper 0317, September.

Bhatty, K., 1998. Educational Deprivation in India: A Survey of Field Investigations, *Economic and Political Weekly,* July 33(28), pp. 1858-1869.

Bourguignon, F., Ferreira, F. and Leite, P., 2002. Ex-ante Evaluation of Conditional Cash Transfer Programs: the Case of Bolsa Escola, The World Bank. Policy Research Working Paper Series 2916.

Calabrese, R.L. 1990, The public school: A source of alienation for minority parents. *The Journal of Negro Education,* 59 (2), pp. 148-154.

Canagarajah, S. and Harold, C., 1999. Child Labor and Schooling in Ghana, The World Bank. Policy Research Working Paper 1844.

Cardoso, E. and Souza, A., 2004. The Impact of Cash Transfers on Child Labor and School Attendance in Brazil, Vanderbilt University, Working Papers 0407, April.

Carvalho, I., 2000. Household Income as a Determinant of Child Labour and School Enrolment in Brazil: Evidence from a Social Security Reform, Massachusetts Institute of Technology.

Cigno, A. and Rosati, F.C., 2000. Why do Indian Children Work, and is it bad for Them? Institute for the Study of Labor (IZA). Discussion Papers No. 115.

Cigno, A., Rosati, F.C. and Zafiris, T., 2001. Child Labor, Nutrition and Education in Rural India: An Economic Analysis of Parental Choice and Policy Options, The World Bank Human Development Network. Social Protection Discussion Paper No. 0131, December.

Das, S. and Mukherjee, D., 2007. Role of women in schooling and child labour decision: the case of urban boys in India, *Social Indicators Research,* vol. 82, no. 3, pp. 463-486.

Doepke, M. and Zilibotti, F., 2009. International labor standards and the political economy of child labor regulation. *Journal of the European Economic Association* 7(2-3), pp. 508-518.

Duflo, E., 2003. Grandmothers and Granddaughters: Old-Age Pensions and Intrahousehold Allocation in South Africa, *World Bank Economic Review,* 17(1), pp. 1-25.

Dumas, C., 2007. Why Do Parents Make Their Children Work? A Test of the Poverty Hypothesis in Burkina Faso, Oxford Economic Papers-New Series, April 59(2), pp. 301-329.

Edmonds, E.V., 2006. Child Labor and Schooling Responses to Anticipated Income in South Africa, *Journal of Development Economics,* December 81(2), pp. 386-414.

Emerson, P.M. and Andre, S., 2008. Birth Order, Child Labor, and School Attendance in Brazil, World Development, September 36(9), pp. 1647-64.

Ersado, L. 2005. Child Labor and Schooling Decisions in Urban and Rural Areas: Comparative Evidence from Nepal, Peru, and Zimbabwe, World Development, March 33(3), pp. 455-480.

Glick, P. and Sahn, D., 1997. Gender and education impacts on employment and earnings in West Africa: Evidence from Guinea, *Economic Development and Cultural Change* 45 (4), pp. 793-823.

Glick, P. and Sahn, D., 2000. Schooling of girls and boys in a West African country: The effects of parental education, income, and household structure, *Economics of Education Review* 19(1), pp. 63-87.

Grootaert, C., 1999. Child Labor in Côte d'Ivoire: Incidence and Determinants, The World Bank. Policy Research Working Paper Series No. 1905.

Handa S. and Davis, B., 2006. The experience of conditional cash transfers in Latin America and the Caribbean. *Development Policy Review* 24(5), pp. 513-536.

Ilahi, N., 2001. Children's Work and Schooling: Does Gender Matter? Evidence from the Peru LSMS Panel Data, The World Bank. Policy Research Working Paper No. 2745, December.

Kabeer, N., Nambissan, G.B. and Subrahmanian, R. (eds.), 2003. *Child Labour and the Right to Education in South Asia: Needs versus Rights?,* New Delhi and London: Sage.

Karabegović, A. and Clemens, J., 2005. Ending Child Labour: Bans Aren't the Solution, The Fraser Forum, March 2005.

Liu, A.Y., 1999. Children's participation behaviour in Vietnam: combined activities. Made available in DSpace on 2011-01-05

López-Calva, L.F., 2001. Child Labor: Myths, Theories and Facts, *Journal of International Affairs,* 55(1).

Lucas, R., 1988. On the mechanics of economic development, *Journal of Monetary Economics* 22, pp. 3-42.

Maluccio, J. and Flores, R., 2005. Impact evaluation of a conditional cash transfer programme: the Nicaraguan Red de Protection Social Research Report 141, International Food Policy Research Institute, Washington DC.

Mankiw, N.G., Romer, D., and Weil, D.N., 1992. A contribution to the empirics of economic growth, *Quarterly Journal of Economics* 107 (2), pp. 407-437.

Maskus, K., 1997. Should core labor standards be imposed through international trade policy? World Bank Development Research Group Policy Research Working Paper 1817, World Bank.

Mukherjee, D. and Das, S. 2008. Role of parental education in schooling and child labour decision: urban India in the last decade, *Social Indicators Research,* Vol. 89, No. 2, pp. 305-322.

Psacharopoulos, G., 1994. Returns to investment in education: A global update, *World Development* 22 (9), pp. 1325-43.

Ravallion, M. and Quentin T.W., 1999. Does Child Labor Displace Schooling? Evidence on Behavioral Responses to an Enrollment Subsidy, The World Bank. Policy Research Working Paper No. 2116, May.

Rawlings L. and Rubio, G., 2005. Evaluating the impact of conditional cash transfer programs: lessons from Latin America. *World Bank Research Observer* 20(1), pp. 29-55.

Ray, Ranjan, 2000. Child Labour, Child Schooling and their Interaction with Adult Labor: Empirical Evidence for Peru and Pakistan, *The World Bank Economic Review*, 14(2): pp. 347-71.

Rosati, F.C. and Zafiris, T. 2006. Child Labour in Vietnam, *Pacific Economic Review,* 11(1), pp. 1-31.

Rubalcava, L., Teruel, G. and Duncan, T., 2009. Impacts of the Oportunidades Program: Investments, Time Preferences, and Public Transfers Paid to Women, *Economic Development and Cultural Change,* 57(3), pp. 507-38.

Schady, N. and Araujo, M.C., 2006. Cash Transfers, Conditions, School Enrollment, and Child Work: Evidence from a Randomized Experiment in Ecuador, The World Bank. World Bank Policy Research Working Paper No. 3930, June.

Siddiqi, F. and Patrinos, H., 1995. Child labor: Issues, causes and interventions, Human Resources and Operations Policy Working Paper 56. Washington, DC: World Bank.

Vijverberg, W.P.W., 1993. Educational investments and returns for women and men in Côte d'Ivoire, *Journal of Human Resources* 28, pp. 933-74.