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DECOMPOSITION OF INCOME-RELATED INEQUALITY IN EDUCATIONAL PERFORMANCE: EVIDENCE FROM INDIA

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Abstract

The present paper analyzes income-related inequality in educational performance of Indian children. Inequality in educational performance shows whether development in education sector is inclusive. We measure inequality in education using the concentration index for scores on standardized tests. Moreover, we use the regression-based decomposition analysis to understand the major contributors to inequality in educational performance. This decomposition analysis quantifies relative contributions of each factor to inequality in educational performance. This analysis is based on the data from the India Human Development Survey. The findings point out importance of parents' education in determining educational performance of child. In particular, inequality in mother's education is one of the major contributors to inequality in educational performance. We also find that economic status of family significantly affects educational performance of the child. Other factors contributing to inequality in educational performance are inequalities in father's education, child health, social background of family, and some school characteristics.

Keywords: Educational Performance, Income-related Inequality, Regression-based Decomposition, India.

JEL Classification: I24, I25

1. Introduction

The objective of present analysis is to estimate income-related inequality in educational performance of Indian children and examine its determinants. Inequality in educational performance indicates whether educational development is inclusive. In this study, we measure the extent of inequality in educational performance across gender and rural-urban sectors. Moreover, based on regression-based decomposition analysis, we estimate percentage contributions of inequality in economic status, parents' education and child health to inequality in educational performance of children.

Inclusive growth has gained importance among the Indian policy makers. Draft report of the Twelfth Five-year Plan talks about inclusive growth which should result in lower incidence of poverty, broad-based and significant improvement in health outcomes, universal access for children to school, increased access to higher education and improved standards of education,

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including skill development (Planning Commission 2011). It is evident that education is one of the main focus areas. Various policies have been adopted to reduce education inequalities. Sarva Shiksha Abhiyan (Education for All), and mid-day meal programme were launched to promote school education and literacy. India has progressed in terms of some of the indicators such as primary school enrollments (Kingdon 2007). At the same time, studies show that inequalities in education are still at high level (Kingdon 2002; Kingdon 2007; Pal and Ghosh 2007; Desai and Kulkarni 2008; Bandyopadhyay and Subrahmanian 2008).

Literature reports presence of gender inequalities in enrollment, and educational attainment[2] in India (Kingdon 2002). Studies suggest that the differential treatment from parents is one of the important causes affecting gender inequality in school enrollment and educational attainment. Moreover, literature examines inequalities in education across different social strata (Desai and Kulkarni 2008). Although these inequalities across social groups are narrowing, they still persist. Above mentioned findings are based on the differential impact of gender or social group on probability of enrollment and completion of certain level of schooling.

Another way to examine the presence of inequalities is to analyse distribution of school enrollment, educational attainment (measured by years of schooling) and educational performance. Studies use the Gini coefficient and the concentration index for educational variables to examine absolute and income-related inequalities in education (Zhang and Li 2002; Sastry and Pebley 2008; Martins and Veiga 2010). Martins and Veiga (2010) use the concentration index to measure the income-related inequalities in educational performance for 15 European countries. They also use the regression-based decomposition to understand how various determinants are contributing to the inequality in education. The present study is based on this literature and examines income-related inequality in educational performance using the concentration index for India. We also use the regression-based decomposition analysis to examine relative role of different contributing factors. Contribution of each factor to income-related inequality in educational performance may be divided into two subcomponents: educational performance elasticity of the factor and income-related inequality of the factor. The government policies affecting any of the two components will have an impact on income-related inequality in educational performance of children. We cannot obtain this division into two subcomponents using standard regression analysis, which emphasizes only on the elasticities of the contributing factors.

For this study, we use India Human Development Study (IHDS) dataset for year 2004-05. Using decomposition analysis, we find how different factors contribute to the inequality in educational performance. We find that economic status of family and mother's education are among the most significant contributors to inequality in mathematics and reading scores. Other factors contributing to inequality in educational performance are inequality in father's education, child health, social background of family, and some school characteristics.

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2 Educational attainment usually refers to the number of years of schooling, whereas educational performance refers to achievement based on test scores.

The rest of the paper is organized as follows: the next section elaborates on the methods of estimating extent of inequalities and decomposition. Section 3 describes the dataset and variables. Section 4 provides empirical findings. Finally, section 5 concludes.

2. Income-related Inequality in Educational Performance

2.1 Data and Methods

Equality in educational performance is important for countries' growth and development (Ibourk and Amaghouss 2013). Some level of inequality may persist due to differences in ability and aptitude. However, systematic inequality in educational performance based on social and economic background is not desirable. We estimate income-related inequality in educational performance of Indian children. This analysis will tell us whether there is any systematic inequality in educational performance based on economic background of children. We use concentration curves to depict the inequality educational performance of children across income. The concentration curve plots the cumulative percentage of education variable against the cumulative percentage of the population, ranked by some income indicator (Wagstaff *et al.* 1991; O'Donnell *et al.* 2008). We can broadly understand the nature of inequality by observing concentration curves. It shows whether better educational performance is concentrated among rich or poor children. However, to measure the extent of inequality and compare it across different subgroups of given population we need to estimate concentration index (CI).

The CI measures the degree of income-related inequality in educational performance. The CI is a bivariate measure that quantifies inequality in educational performance present across distribution of population based on some income indicator. Thus, the CI provides a measure of the extent of inequalities in education that are systematically related to income status (Wagstaff *et al.* 1991). The CI is extensively used in health economics literature for examining income-related inequality in health[3] (see e.g. Wagstaff *et al.* 1991; van Doorslaer and Jones 2003; Wagstaff and van Doorslaer 2004; van Doorslaer *et al.* 2004; Hooseinpoor *et al.* 2006). In the present paper, we use the CI to measure income-related inequality in educational performance of children. The CI is defined as twice the area between the concentration curve and the line of equality and it is estimated as:

$$CI = \frac{2}{\mu}\text{cov}(X_i, R_i) \qquad \text{... (1)}$$

where, X_i indicates a measure of educational performance, μ is the mean score representing educational performance and R_i is child's relative rank based on income indicator.

To measure the concentration index for educational performance, we use the India Human Development Survey (IHDS). This survey was jointly conducted by the National Council of Applied Economic Research (NCAER) and the University of Maryland, College Park during period 2004-2005. It is a nationally representative sample survey covering 41,554 households from all states and union territories of India.

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3 Recently, studies have used concentration index to measure income-related inequality in education (Martins and Veiga 2010) and financial inclusion (Pal and Pal 2012). However, literature on inequality in education is sparse.

Educational performance is estimated using scores on standardized tests for mathematics and reading. The survey provides information on standardized test scores for children between age group eight to 11. These test scores are used to evaluate educational performance of a child. Moreover, since tests were conducted only for children between eight to 11 years of age, we have restricted the present analysis to these children.

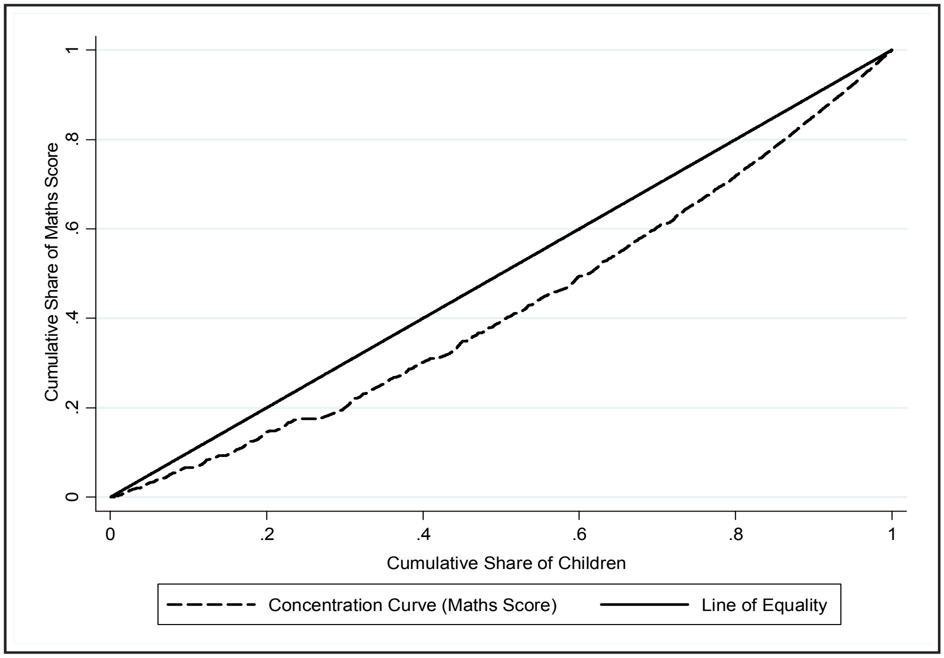
To measure income-related inequality in educational performance, we need an economic indicator to rank children. The data gives information on different assets possessed by households such as cycle, sewing machine, generator set, mixer/grinder, motor cycle, black and white television, colour television, air cooler, clock and watch, electric fan, chair/table, cot, telephone, cell phone, refrigerator, and pressure cooker. Using this information, we construct a wealth index based on principal components analysis as proposed by Filmer and Pritchett (2001). This wealth index is used to rank children while measuring inequality. Thus, we measure income-related inequality in educational performance where wealth index is taken as income indicator. This analysis allows us to understand how the distribution of educational performance varies across income status.

Moreover, since the data is collected using sampling techniques, we use sampling weights provided in the dataset while estimating concentration indices to make the data nationally representative.

2.2 Concentration Curve and Concentration Index for Educational Performance

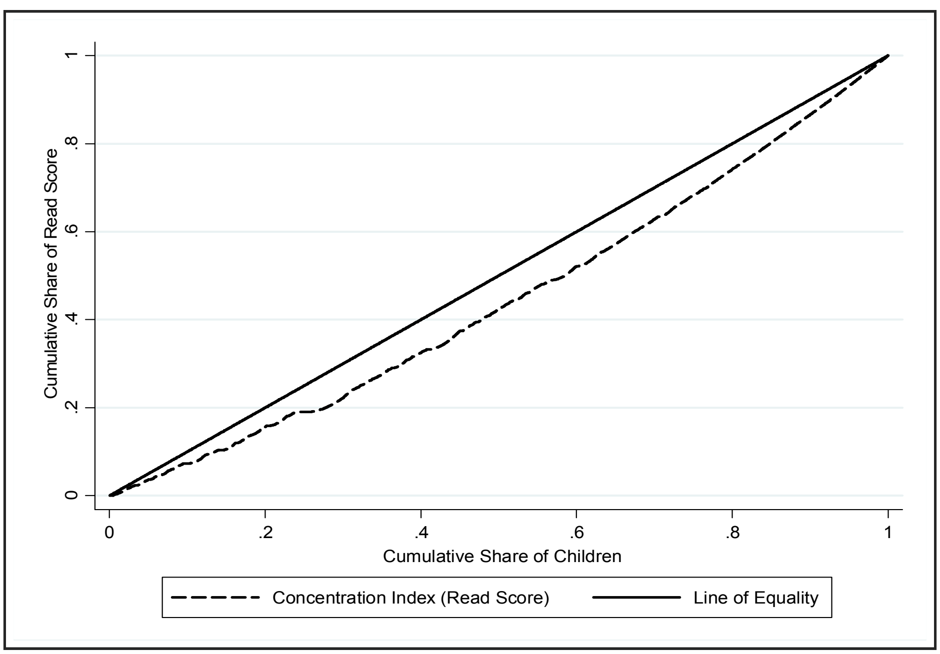
The educational performance for Indian children is measured using scores on standardized tests for mathematics and reading. Figure 1 and Figure 2 show the presence of income-related inequality in educational performance of Indian children. The concentration curves for scores on both mathematics and reading tests lie below the line of equality. Equity in education requires that educational performance measured by test scores varies only with ability of the student and do not vary systematically certain background characteristics such as economic and social status. However, it is evident from the figures that test scores differ across economic status and better educational performance is concentrated among rich children. This result indicates existence of inequality of opportunity in India. Since education performance is influenced by economic background, both rich and poor children do not get the same opportunity to perform at schools.

Next, we analyse gender-wise inequality in educational performance using the concentration indices. We find that distribution of educational performance is more unequal for girls (CI is 0.173 for mathematics scores) than for boys (CI is 0.117 for mathematics scores) and distribution is favourable to rich children (Table 1). This result suggests that inequality of opportunity is higher for girls as compared to boys. Discrimination at household level against girl child may result in lack of opportunity to study and perform better. For instance, Kingdon (2002) and Bandyopadhyay and Subrahmanian (2008) report inequality in educational enrollment and attainment across gender due to intra-household discrimination present in India. Moreover, South Asia Human Development Sector (2004) points out importance of inequality in access to other factors such as nutrition, immunization and health care that result in gender inequality in educational performance.



Source: Estimation based on IHDS-2004-05 dataset.

Figure 1. Income-related Inequality in Mathematics Scores



Source: Estimation based on IHDS-2004-05 dataset.

Figure 2. Income-Related Inequality in Reading Scores

Table 1. Concentration Indices for Educational Performance

	Mathematics Score	*Reading Score*
Male	0.117	0.086
Female	0.173	0.129
Rural	0.127	0.117
Urban	0.118	0.085
India	**0.141**	**0.106**

Source: Estimation based on IHDS-2004-05 dataset.

Secondly, comparing concentration indices across sectors, we find that inequality in educational performance is more in rural areas as compared to urban areas. For instance, concentration index for mathematics score in rural areas is 0.127 and in urban India, it is 0.118. This finding shows that poor children have greater opportunity to perform better if they are from urban areas as compared to rural areas. Studies (for instance, The World Bank 2003; Hnatkovska and Lahiri 2013) report higher school enrolment in urban areas as compared to rural India. We find that it is not only enrolment and attainment level that is different, but the inequality in educational performance differs across the two sectors. This might be due to greater availability and accessibility to good schools in urban areas. For instance, Desai and Kulkarni (2008) reports that in urban India availability and quality of schools is better as compared to rural India.

This sub-section shows inequality in educational performance differs across gender and regions. Female children and children from rural areas experience greater inequality in opportunity. The next important question is regarding factors contributing to these inequalities. We want to understand the determinants of educational performance and their contribution to income-related inequality in educational performance. The following section elaborates on decomposition analysis which will help us understand contribution of each factor and reports the estimated relative contributions of various factors to inequality in education.

3. Decomposing Income-related Inequality in Educational Performance

After estimation of income-related inequality in educational performance, the next task is to analyze factors that contribute to this inequality. We use the regression-based decomposition method to examine contribution of various factors to inequality in educational performance. In this method, the first step is to estimate a regression model for dependent variable, educational performance. And the second step involves decomposition of inequality and estimation of contributions from various determinants. Wagstaff *et al.* (2003) shows that in a linear regression model

$$y_i = \alpha + \sum_k \beta_k x_{ki} + \varepsilon_i \qquad \text{... (1)}$$

the concentration index may be decomposed as

$$C = \sum_k \left(\frac{\beta_k \bar{x}_k}{\mu} \right) C_k + \frac{GC_\varepsilon}{\mu} = C_{\hat{y}} + \frac{GC_\varepsilon}{\mu} \qquad \text{... (2)}$$

where μ is the mean of y, $\bar{x}_k$ is the mean of x_k, C_k is the CI for x_k, and GC_ε is the generalized CI for ε. The equation 3 shows that the CI for variable y may be decomposed into two components: explained and unexplained. The explained component is a weighted sum of individual CIs for all regressors x. This component shows how much of the income-related inequality may be explained by (i) elasticity of y variable with respect to x_k, and (ii) income-related inequality in variable x_k. The unexplained component is the generalized CI for disturbance term. It may be noted that this decomposition procedure is only valid if the regression equation is linear.

In the present paper, we estimate regression models for scores on standardized tests for mathematics and reading. These two variables are ordered discrete variables. As a result, linear regression model is not useful in this context. To examine determinants of test scores and decompose the inequality in test scores, we estimate an ordered probit model. The underlying latent variable regression may be specified as:

$$y_i^* = x_i\beta + \varepsilon_i \qquad \text{... (4)}$$

where, y^* is the unobserved latent variable determining test scores. Vector x is the vector of explanatory variables and β is the vector of associated coefficients. The term ε is the error term. We observe the test score and it is given by;

$$\begin{aligned} y_i &= 0 \quad \text{if } y_i^* \le 0 \\ &= 1 \quad \text{if } 0 < y_i^* \le \delta_1 \\ &= 2 \quad \text{if } \delta_1 < y_i^* \le \delta_2 \qquad \text{... (3)} \\ &\dots \\ &= J \quad \text{if } \delta_{J-1} < y_i^* \end{aligned}$$

In the above model, δs are unknown parameters like βs which we need to estimate. In the ordered probit model the assumption is that the error term is normally distributed. Thus, the probability of observing a particular value of y is given by;

$$P_{ij} = P(y_i = j) = \Phi(\delta_j - x_i\beta) - \Phi(\delta_{j-1} - x_i\beta) \qquad \text{... (4)}$$

where $\Phi(.)$ is the standard normal distribution function.

It may be noted the regression model specified by equation 4, 5 and 6 is not linear as in the equation 2. As a result, it is not possible to carry out the decomposition analysis using equation 3 for dependent variable y. However, the predictions $x_i\hat{\beta}$ are linear in x_is, so it is possible to decompose these linear predictions. This method is suggested by (van Doorslaer and Jones 2003). We follow this method in the present study to decompose the inequality in educational performance and estimate the contribution of various factors to inequality in educational performance. We must note here that this procedure allows only the explained part of total inequality in educational performance to be decomposed. Moreover, as noted by O'Donnell *et al.* (2003), decomposition results are dependent on the point at which marginal effects are evaluated. In the present study, following literature, we evaluate marginal effects at the mean of explanatory variables.

3.1 Explanatory Variables

For the decomposition analysis, we consider various explanatory variables such as characteristics of child, schooling characteristics, family characteristics, and regional characteristics to explain and decompose inequality in education. Variables in each of the above categories are explained below.[4]

Table 2. Definitions of Variables

Variable	*Definition*
Mathematics Scores	= 0 if child does not know any mathematics, = 1 if child can recognize numbers, = 2 if child can do subtraction, = 3 if child can do division
Reading Scores	= 0 if child cannot read, = 1 if child can read letters, = 2 if child can read words, = 3 child can read a paragraph, = 4 if child can read entire story
Stunted	= 1 if child is stunted, = 0 otherwise
Gender (Base category: male)	= 1 if child is female, = 0 child is male
Distance from School	Distance in kilometers
Education Expenditure	Total amount spend for the education of child in rupees
Government School	= 1 if child goes to a government school, =0 otherwise
English Medium	= 1 if medium of instruction at school is English, = 0 otherwise
No. of Days Absent	Number of days in previous month child is absent from school
No. Study Hours Per Week	Total number of hours spent in studying during the week
School Standard	Child's school standard.
Education of Father	Education of father of child (in years)
Education of Mother	Education of mother of child (in years)
Wealth Index	Index of wealth based on ownership of durable goods
Poor	= 1 if family is below poverty line, = 0 otherwise
Brahmin	= 1 if family belongs to the caste category 'Brahmin', =0 otherwise
OBC	= 1 if family belongs to the caste categories 'Other Backward Classes', =0 otherwise
SC	= 1 if family belongs to the caste categories 'Other Backward Classes', =0 otherwise
ST	= 1 if family belongs to the caste categories 'Other Backward Classes', =0 otherwise
Urban (Base category: Rural)	= 1 if family resides in urban areas, = 0 otherwise
Urban Slum	= 1 if family resides in urban slums, = 0 otherwise
Bimaru	= 1 if family resides in less developed states, namely, Bihar, Madhya Pradesh, Orissa, Rajasthan and Uttar Pradesh, = 0 otherwise

[4] Detailed definitions of all the variables are explained in Table 2.

Characteristics of Child

Child characteristics such as health and gender are likely to affect scores on mathematics and reading tests. Literature finds close relation between child health and educational performance of children (for instance, see, Alderman *et al.* 2001; Glewwe and Jacoby 1995; Glewee *et al.* 1999; Glewwe *et al.* 2001). To examine contribution of inequality in child health to inequality in educational performance, we use anthropometric measures of health. The dataset provides information on anthropometric measures of health such as height and weight. We measure child health using presence of malnutrition based on height-for-age criterion. We compare the height-for-age to the standards provided by the World Health Organization (WHO). Literature considers a child 'stunted' (and hence malnourished) if child's height is below 2-standard deviations of standard height for his/her age (WHO Working Group 1986; Wamani *et al.* 2004; de Onis *et al.* 2011). We follow the literature and define 'stunting' variable in the same way. This binary variable is useful since it incorporates differentiated standards across gender. It is not possible to incorporate this with continuous variable height-for-age. This 'stunting' variable thus measures malnutrition in children after incorporating age and gender differences. Presence of malnutrition is likely to result in perpetual low health of child which in turn affects educational performance of child. Thus, we expect to find negative relation between presence of malnutrition and test scores.

Along with health, we also include gender as an explanatory variable in the regression analysis. Inclusion of gender allows us to examine presence of gender difference in educational performance. Gender gap in educational performance may be observed due to differentiated intra-household treatment to boys and girls (Kingdon 2002). Apart from including a dummy variable, we examine whether the impact of other explanatory variables on test scores is different for girls and boys using separate regression analysis across gender.

Schooling Characteristics

Studies point out that performance of child varies across public and private schools (Kingdon 1998; Goyal 2010). We include a dummy variable for government school to examine impact of type of school on educational performance. We also consider other school-related characteristics such as distance from school, total spending on education of child, years of education as denoted by standard in which child is studying, number of days child was absent from school in the last month, and weekly number of hours spent on study.

Household Characteristics

Family background also matters for educational performance of a child. Literature shows positive relation between education of parents and performance of child (Martins and Veiga, 2010). Unlike most of the datasets on India, the present dataset provides information on relation among family members and thus allows us to include education of father and mother of child.

Apart from education level, socio-economic status of family influences educational opportunities and achievements of child. To capture these effects, we include wealth index quantile groups and a binary variable if household is below poverty line in the regression. We also include four caste variables to examine impact of social background of household.

Parental education and socio-economic background show equality in educational opportunity for children (Asadullah and Yalonetzky 2010). For instance, if parental education is a major determinant of education performance of child, then children with low parental education have lower educational opportunity as compared to the children with high parental education.

Regional Characteristics

We include two binary variables 'Urban' and 'Urban Slums' to analyse the rural-urban differences. Since urban slums usually lack basic amenities of health care and elementary schooling, we separate the slums in the urban areas. Rural areas are taken as base category.

Secondly, we include a binary variable 'BIMARU' to capture the differential health and educational status in less-developed states, namely, Bihar, Madhya Pradesh, Orissa, Rajasthan and Uttar Pradesh.

3.2 Empirical Findings

Table 3 presents results of the decomposition analysis for educational performance. The decomposition analysis is carried out separately for scores on mathematics and reading tests. We have reported coefficients of explanatory variables in the ordered probit regression, elasticity, concentration index for explanatory variables and percentage contribution of explanatory variable to inequality test scores. The results show that education of mother, years of schooling and economic status of household are the major contributors to inequality in educational performance. Moreover, we find negative and significant impact of stunting on test scores. Inequality in child health positively contributes to inequality in test scores, although the contribution is small as compared to the other factors.

Education of parents plays an important role in determining performance of child on test scores. It also contributes significantly to the explained inequality in test scores. For instance, the contributions of mother's education are 17.7 percent and 23.8 percent of total explained inequality in educational performance based on mathematics scores and reading scores, respectively. At the same time, empirical findings suggest that the father's education is not as important contributor as mother's education. Father's education contributes only 11.6 percent and 9.5 percent to total explained inequality in mathematics and reading scores, respectively. These results are similar to Kingdon (2002), which shows importance of parental education on years of education completed by child in India.[5] Kingdon (2002) shows that both mother's and father's education have significant impact on years of education completed by girl child, however only father's education is important for boy child. Contrary to this, we find that mother's education has significant impact on both boy and girl child's education (Table 4 and 5). Also, when we consider contribution to educational inequality we find that mother's education is more important than father's education. These results point out importance of female education. If income-related inequality in female education is reduced, it will have larger impact on inequality in educational performance than the similar reduction in inequality in male education.

[5] Studies on other countries also report importance of parental education on educational performance of children (for instance, Cameron and Heckman, 2001, Chevalier, 2004, and Martins and Veiga, 2010).

Table 3. Decomposition of Inequality in Educational Performance
(Mathematics and Reading Scores)

	Mathematics Score				*Reading Score*			
Variable	*Coeff.*	*Elasticity*	*CI for X*	*Contribution*	*Coeff.*	*Elasticity*	*CI for X*	*Contribution*
Child Characteristics								
Stunted	-0.106*	-0.029	-0.089	0.012	-0.232**	-0.057	-0.064	0.022
Gender	-0.190**	-0.077	-0.003	0.001	-0.128**	-0.045	-0.002	0.001
Schooling Characteristics								
Distance from School	0.012	0.016	0.082	0.006	0.038**	0.043	0.091	0.020
Education Expenditure	0.000	0.026	0.428	0.051	0.000	0.004	0.381	0.010
Government School	-0.217**	-0.128	-0.151	0.088	-0.212**	-0.110	-0.097	0.093
English Medium	0.017	0.001	0.521	0.003	0.007	0.000	0.529	0.002
No. of Days Absent	-0.009	-0.028	-0.158	0.020	-0.006	-0.015	-0.096	0.012
No. Study Hours Per Day	0.006**	0.169	0.081	0.062	0.007**	0.173	0.064	0.062
School Standard	0.331**	0.865	0.071	0.281	0.351**	0.805	0.062	0.238
Family Characteristics								
Education of Father	0.020**	0.099	0.256	0.116	0.016**	0.070	0.241	0.095
Education of Mother	0.037**	0.103	0.377	0.177	0.047**	0.114	0.371	0.238
Wealth Class 2	0.010	0.002	-0.321	-0.002	0.057	0.009	-0.175	-0.015
Wealth Class 3	0.089	0.014	0.136	0.009	0.082	0.011	0.316	0.008
Wealth Class 4	0.224**	0.033	0.559	0.085	0.242**	0.032	0.697	0.093
Wealth Class 5	0.235**	0.028	0.908	0.115	0.272**	0.028	0.958	0.141
Poor	-0.212**	-0.054	-0.343	0.085	-0.152**	-0.034	-0.328	0.059
Brahmin	0.262*	0.011	0.417	0.021	0.163	0.006	0.410	0.013
OBC	-0.032	-0.011	0.009	0.000	-0.033	-0.011	0.015	0.000
SC	-0.142*	-0.028	-0.192	0.025	-0.102	-0.018	-0.131	0.016
ST	-0.097	-0.006	-0.352	0.009	0.054	0.003	-0.317	-0.005
Regional Characteristics								
Urban	0.047	0.008	0.412	0.016	0.052	0.008	0.418	0.018
Urban Slum	-0.133	-0.002	0.197	-0.002	-0.046	-0.001	0.186	-0.001
Bimaru	0.240**	0.074	-0.165	-0.056	0.253**	0.069	-0.151	-0.059
Pseudo R^2			0.136				0.121	
No. of Observations			5851				5871	
Linear Prediction (CI)			0.219				0.186	
Linear Prediction (Mean)			1.173				1.336	
Linear Prediction (S.D.)			0.726				0.740	

Source: Estimation based on IHDS-2004-05 dataset.

Note: ** are significant at 5 percent level of significance.

Economic status of family is another important determinant of educational performance. Results show positive relation between economic status of family and test scores. The contribution of wealth index quintiles to explained inequality in test scores is also large at around 20 percent for mathematics scores (Table 3). Literature reports positive effect of economic status on school enrolments in India (Filmer and Pritchett 2001).[6] We find that impact of economic status is not limited to enrolments but it also affects educational performance of children. Similarly, in correspondence with literature we find that social background affects educational performance of children.[7] Results show that children from socially deprived classes have lower test scores, on an average, as compared to others. At the same time, contribution of social background is not as high as that of economic status towards inequality in educational performance.

Apart from parent's education and economic status of family, child health affects educational performance. The results show negative impact of stunting on test score in both the cases. Kingdon (2002) also reports similar result that child health affects probability of enrolment for male child in India. Decomposition analysis allows us to go one step further and understand how important child health is for inequality in educational performance. The results show that income-related inequality in child health (stunting) makes positive contribution to income-inequality in educational performance. The contribution of health inequality is 1.2 percent and 2.2 percent in the case of inequality in mathematics and reading scores, respectively. These results provide some evidence of correlation between education and health inequalities.[8] At the same time, it may be noted that contribution of child health to inequality in educational performance is very small as compared to educational background of parents and family's socio-economic status.

Furthermore, school characteristics are important contributors of inequality in educational performance. Years of schooling are the most important contributor to inequality in test score. This result is obvious, as years of schooling increase child is likely to perform better on test scores. Thus, inequality in years of schooling explains large portion of inequality in test scores.[9] We also find that the type of schooling matters to the educational performance of children. Government schools have negative impact on test scores and the percentage contributions of government schools to inequality in educational performance are 8.8 and 9.3 percent for mathematics and reading test scores, respectively.

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6 Results based on 15 European countries also show that economic background of family contributes towards educational performance, measured by test scores for mathematics (Martins and Veiga, 2010).

7 For instance, Filmer and Pritchett (2001) shows lower probability of school enrolment for children from socially deprived classes. Kingdon (2002) finds that if person belongs to socially deprived class then probability of enrolment is lower as well as years of education completed is also lower.

8 We find no difference between girl and boy child as far as contribution of child health to education inequality is concerned (Table 4 and 5).

9 We also estimated separate regression models according to the year of schooling. We find that the results are qualitatively same, as the coefficient and contribution of other variables do not change in sign and significance.

We also carry out the decomposition analysis separately across gender to throw light on the differential impact of health inequality on educational inequality. Table 4 and table 5 show the results of this decomposition analysis for scores on mathematics tests and reading tests, respectively. Results show that the contribution of inequality in mother's education to inequality in mathematics score is higher for girl child (24.1 percent) as compared to the boy child (12.2 percent). For reading score, the findings are similar. At the same time, contribution of inequality in father's education is consistently lower as compared to mother's education towards the inequality in educational performance of girl child.

Comparison across rural-urban sectors provides some interesting results (Table 6 and 7). The findings show that inequality in mother's education contributes to a much higher proportion in urban areas as opposed to the rural areas for both mathematics and reading scores. In urban areas, the percentage contributions of mother's education are 25.7 percent for mathematics score and 38.4 percent for reading score. In the rural sector, the percentage contributions are much lower at 16.2 and 20.7 percent for mathematics and reading scores, respectively. These findings suggest that reducing inequality in female education is much more important reduce inequality in educational performance of a child in urban areas.

4. Concluding Remarks

The present paper examines inequalities in educational performance for Indian children. We find the presence of income-related inequality in educational performance in India and it is unfavourable to poor children. Based on regression-based decomposition analysis, we find that inequality in mother's education and wealth index classes are the most important contributors to inequality in educational performance. We also find that the contribution of inequality in mother's education to inequality in mathematics score is higher for girl child (24.1 percent) as compared to the boy child (12.2 percent). Moreover, mother's education matters more in the urban sector. These results indicate that increasing overall education levels of female may help reducing inequalities in educational performance of children.

At the same time, the income-related inequalities in educational performance are also related to the inequalities in income and health. We find that economic background, represented by the wealth index, is one of the major contributing factors to inequality in educational performance. Moreover, inequality in child health contributes positively to inequality in test scores. This interrelation among inequalities in education, income and health warrants proper integration of various developmental policies. Simultaneous reduction in all the three types of inequalities will result in faster inclusive development.

Table 4. Decomposition of Inequality in Mathematics Scores (across Gender)

	Male				*Female*			
Variable	*Coeff.*	*Elasticity*	*CI for X*	*Contribution*	*Coeff.*	*Elasticity*	*CI for X*	*Contribution*
Child Characteristics								
Stunted	-0.180**	-0.044	-0.063	0.014	-0.019	-0.005	-0.084	0.002
Schooling Characteristics								
Distance from School	0.005	0.007	0.092	0.003	0.017	0.019	0.086	0.008
Education Expenditure	0.000	0.014	0.460	0.032	5.6E-05**	0.041	0.477	0.094
Government School	-0.307**	-0.163	-0.168	0.141	-0.109	-0.061	-0.146	0.042
English Medium	-0.032	-0.003	0.571	-0.008	0.067	0.004	0.591	0.012
No. of Days Absent	-0.007	-0.020	-0.123	0.013	-0.011	-0.031	-0.160	0.023
No. Study Hours Per Day	0.007**	0.200	0.059	0.061	0.004	0.110	0.082	0.043
School Standard	0.353**	0.854	0.051	0.223	0.315**	0.751	0.071	0.255
Family Characteristics								
Education of Father	0.032**	0.143	0.249	0.183	0.008	0.038	0.256	0.046
Education of Mother	0.023**	0.059	0.399	0.122	0.053**	0.134	0.377	0.241
Wealth Class 2	0.126	0.020	-0.317	-0.033	-0.133	-0.021	-0.324	0.032
Wealth Class 3	0.072	0.010	0.136	0.007	0.104	0.015	0.134	0.010
Wealth Class 4	0.208*	0.028	0.551	0.080	0.256**	0.035	0.554	0.093
Wealth Class 5	0.262**	0.029	0.926	0.138	0.208*	0.023	0.911	0.098
Poor	-0.254**	-0.058	-0.322	0.096	-0.170*	-0.042	-0.330	0.065
Brahmin	0.261	0.010	0.426	0.021	0.257	0.010	0.400	0.020
OBC	-0.002	-0.001	-0.004	0.000	-0.069	-0.023	0.010	-0.001
SC	-0.209**	-0.037	-0.145	0.028	-0.089	-0.017	-0.184	0.015
ST	-0.085	-0.005	-0.391	0.009	-0.141	-0.008	-0.346	0.013
Regional Characteristics								
Urban	0.000	0.000	0.420	0.000	0.083	0.013	0.418	0.027
Urban Slum	-0.122	-0.002	0.242	-0.002	-0.134	-0.002	0.186	-0.002
Bimaru	0.207	0.059	-0.156	-0.047	0.262**	0.075	-0.163	-0.058
Pseudo R^2			0.138				0.139	
No. of Observations			3103				2748	
Linear Prediction (CI)			0.194				0.210	
Linear Prediction (Mean)			1.265				1.279	
Linear Prediction (S.D.)			0.747				0.734	

Source: Estimation based on IHDS-2004-05 dataset.

Note: ** are significant at 5 percent level of significance.

Table 5. Decomposition of Inequality in Reading Scores (across Gender)

	Male				*Female*			
Variable	*Coeff.*	*Elasticity*	*CI for X*	*Contribution*	*Coeff.*	*Elasticity*	*CI for X*	*Contribution*
Child Characteristics								
Stunted	-0.223**	-0.048	-0.063	0.019	-0.236**	-0.060	-0.084	0.025
Schooling Characteristics								
Distance from School	0.035**	0.039	0.092	0.022	0.038	0.040	0.086	0.017
Education Expenditure	-6.5E-07	-0.001	0.458	-0.001	2.0E-05	0.014	0.477	0.034
Government School	-0.271**	-0.127	-0.168	0.133	-0.151	-0.080	-0.146	0.058
English Medium	-0.104	-0.008	0.567	-0.027	0.160	0.010	0.589	0.029
No. of Days Absent	-0.002	-0.004	-0.123	0.003	-0.010	-0.026	-0.160	0.021
No. Study Hours Per Day	0.007**	0.183	0.059	0.067	0.006*	0.141	0.082	0.058
School Standard	0.354**	0.759	0.051	0.239	0.352**	0.797	0.071	0.284
Family Characteristics								
Education of Father	0.028**	0.111	0.249	0.171	0.005	0.021	0.256	0.026
Education of Mother	0.041**	0.092	0.399	0.229	0.053**	0.128	0.377	0.241
Wealth Class 2	0.155*	0.022	-0.318	-0.044	-0.064	-0.009	-0.324	0.015
Wealth Class 3	-0.012	-0.001	0.136	-0.001	0.173	0.024	0.134	0.016
Wealth Class 4	0.237**	0.029	0.550	0.098	0.240**	0.031	0.554	0.087
Wealth Class 5	0.264**	0.026	0.923	0.148	0.269**	0.028	0.913	0.126
Poor	-0.163**	-0.033	-0.322	0.066	-0.139**	-0.032	-0.330	0.053
Brahmin	0.144	0.005	0.427	0.013	0.170	0.006	0.399	0.013
OBC	0.035	0.010	-0.004	0.000	-0.108	-0.034	0.010	-0.002
SC	-0.086	-0.014	-0.145	0.012	-0.125	-0.022	-0.184	0.021
ST	0.082	0.004	-0.391	-0.010	0.006	0.000	-0.345	-0.001
Regional Characteristics								
Urban	-0.013	-0.002	0.418	-0.005	0.107	0.016	0.418	0.034
Urban Slum	-0.102	-0.001	0.241	-0.002	-0.018	0.000	0.186	0.000
Bimaru	0.210**	0.053	-0.156	-0.051	0.287**	0.078	-0.163	-0.064
Pseudo R^2		0.117				0.129		
No. of Observations		3115				2756		
Linear Prediction (CI)		0.161				0.200		
Linear Prediction (Mean)		1.431				1.349		
Linear Prediction (S.D.)		0.732				0.768		

Source: Estimation based on IHDS-2004-05 dataset.

Note: ** are significant at 5 percent level of significance.

Table 6. Decomposition of Inequality in Mathematics Scores (across Rural-Urban Sectors)

	Rural				*Urban*			
Variable	*Coeff.*	*Elasticity*	*CI for X*	*Contribution*	*Coeff.*	*Elasticity*	*CI for X*	*Contribution*
Child Characteristics								
Stunted	-0.099	-0.027	-0.064	0.009	-0.126*	-0.035	-0.069	0.012
Gender	-0.232**	-0.089	-0.002	0.001	-0.059	-0.026	-0.021	0.003
Schooling Characteristics								
Distance from School	-0.004	-0.005	0.091	-0.003	0.050*	0.074	0.102	0.038
Education Expenditure	8.4E-05**	0.048	0.381	0.097	1.5E-05	0.031	0.415	0.066
Government School	-0.238**	-0.148	-0.097	0.076	-0.104	-0.041	-0.264	0.055
English Medium	-0.166	-0.007	0.529	-0.018	0.173*	0.040	0.427	0.087
No. of Days Absent	-0.010	-0.033	-0.096	0.017	-0.010	-0.021	-0.149	0.016
No. Study Hours Per Day	0.006**	0.177	0.064	0.060	0.004	0.158	0.062	0.050
School Standard	0.350**	0.849	0.062	0.278	0.270**	0.818	0.053	0.219
Family Characteristics								
Education of Father	0.019**	0.078	0.241	0.099	0.023**	0.166	0.219	0.185
Education of Mother	0.042**	0.083	0.371	0.162	0.032**	0.173	0.291	0.257
Wealth Class 2	0.003	0.001	-0.175	-0.001	-0.040	-0.002	-0.931	0.011
Wealth Class 3	0.072	0.011	0.316	0.019	0.090	0.013	-0.641	-0.042
Wealth Class 4	0.143	0.018	0.697	0.065	0.336**	0.079	-0.082	-0.033
Wealth Class 5	0.223**	0.015	0.958	0.077	0.229**	0.071	0.724	0.261
Poor	-0.159**	-0.039	-0.328	0.067	-0.358**	-0.100	-0.440	0.225
Brahmin	0.322*	0.011	0.410	0.024	0.174	0.012	0.349	0.021
OBC	-0.018	-0.006	0.015	0.000	-0.067	-0.026	-0.064	0.009
SC	-0.148*	-0.030	-0.131	0.021	-0.129	-0.022	-0.213	0.024
ST	-0.087	-0.006	-0.317	0.010	-0.120	-0.003	-0.170	0.003
Regional Characteristics								
Bimaru	0.246**	0.078	-0.151	-0.062	0.182**	0.045	-0.110	-0.025
Pseudo R^2			0.131				0.128	
No. of Observations			4039				1812	
Linear Prediction (CI)			0.189				0.196	
Linear Prediction (Mean)			1.243				1.058	
Linear Prediction (S.D.)			0.780				0.688	

Source: Estimation based on IHDS-2004-05 dataset.

Note: ** are significant at 5 percent level of significance.

Table 7. Decomposition of Inequality in Reading Scores (across Rural-Urban Sectors)

	Rural				*Urban*			
Variable	*Coeff.*	*Elasticity*	*CI for X*	*Contribution*	*Coeff.*	*Elasticity*	*CI for X*	*Contribution*
Child Characteristics								
Stunted	-0.224**	-0.052	-0.064	0.021	-0.247**	-0.064	-0.069	0.026
Gender	-0.175**	-0.058	-0.002	0.001	0.019	0.008	-0.021	-0.001
Schooling Characteristics								
Distance from School	0.038**	0.040	0.090	0.023	0.021	0.030	0.102	0.018
Education Expenditure	4.5E-05	0.022	0.380	0.055	5.4E-07	0.001	0.414	0.003
Government School	-0.242**	-0.130	-0.097	0.081	-0.101	-0.038	-0.265	0.058
English Medium	-0.022	-0.001	0.525	-0.003	0.037	0.008	0.426	0.020
No. of Days Absent	-0.005	-0.014	-0.096	0.009	-0.006	-0.011	-0.149	0.009
No. Study Hours Per Day	0.008**	0.200	0.064	0.082	0.002	0.079	0.062	0.028
School Standard	0.378**	0.794	0.062	0.315	0.265**	0.755	0.052	0.230
Family Characteristics								
Education of Father	0.016*	0.056	0.241	0.087	0.021**	0.144	0.219	0.182
Education of Mother	0.050**	0.087	0.370	0.207	0.045**	0.227	0.291	0.384
Wealth Class 2	0.027	0.005	-0.175	-0.005	0.229	0.012	-0.928	-0.066
Wealth Class 3	0.045	0.006	0.316	0.012	0.149	0.020	-0.641	-0.074
Wealth Class 4	0.165*	0.017	0.696	0.078	0.380**	0.083	-0.082	-0.040
Wealth Class 5	0.177	0.010	0.956	0.064	0.408**	0.119	0.725	0.499
Poor	-0.148**	-0.031	-0.329	0.066	-0.155*	-0.041	-0.440	0.104
Brahmin	0.162	0.005	0.410	0.013	0.218	0.014	0.349	0.029
OBC	-0.055	-0.016	0.015	-0.002	0.020	0.007	-0.064	-0.003
SC	-0.131	-0.023	-0.132	0.019	-0.018	-0.003	-0.213	0.004
ST	0.071	0.004	-0.317	-0.008	-0.175	-0.004	-0.170	0.004
Regional Characteristics								
Bimaru	0.288**	0.079	-0.151	-0.076	0.071	0.016	-0.110	-0.011
Pseudo R^2		0.122				0.099		
No. of Observations		4053				1818		
Linear Prediction (CI)		0.155				0.172		
Linear Prediction (Mean)		1.437				1.126		
Linear Prediction (S.D.)		0.799				0.642		

Source: Estimation based on IHDS-2004-05 dataset.

Note: ** are significant at 5 percent level of significance.

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