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Child Schooling in India: Is there any evidence of a gender bias?

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ABSTRACT

The aim of this paper is to analyse factors that influence schooling outcomes among children in India, specifically focusing on the role of gender. Using the nationally representative *Indian National Family Health Survey 2005-06,*our analysis finds statistically significant evidence of male advantage both in schooling attendance as well as years of schooling. However, using a cluster fixed-effects model, our analysis finds that within a cluster, contingent on being enrolled, girls spend more years in school relative to boys. Other results show that parental schooling has a positive and statistically significant impact on child schooling. There is also statistically significant wealth effect, community effect and regional disparities between states in India.

Keywords: child schooling; cluster fixed effects; household fixed effects; gender bias
JEL Codes: J16, J24, O15, I20, D13

1. Introduction

The Indian economy has grown at a rapid pace over the last two decades. However, educational outcomes continue to be poor for large sections of the population, and this is presenting a tremendous policy challenge in efforts to increase economic growth even further. Moreover, there are problems not just with low enrolment rates at the primary school level, but also with low retention rates at the primary, secondary and higher secondary school levels. Implicit in this scenario are the very high drop-out rates for school age children. A recent study by the UNDP (2012) has found that the mean years of schooling in India to be just 4.4 years. The recent census figures show continued gender disparities in education and health outcomes, high levels of poverty and inequity in economic growth (Chaudhri and Jha, 2011).

The problem of low child schooling in India has been widely documented in the literature (see Dostie and Jayaraman, 2006; Borooah and Iyer, 2005; Pal, 2004b; Kambhampati and Pal, 2001; Kingdon, 1998). There is overwhelming evidence of gender disparities in educational outcomes in India, with wide heterogeneity across Indian states with regards to both schooling levels and the gender disparities in these. For example, studies by Sundaram and Vanneman (2008), Kingdon (2007) and Dommaraju and Agadjanian (2009) find that although gender differentiated educational outcomes are observed in all the Indian states, the gender gaps in education are particularly large in the Northern states relative to the Southern states. However, to our knowledge there is no study that has examined if these gender differences persist among children from the same cluster or community.

In this paper we use data from the nationally representative *Indian National Family and Health Survey* (NFHS-2 and 3) collected in 1998-99 and 2005-06 to analyse the factors influencing school enrolment, progression and retention. In particular our analysis examines if there is any evidence of gender differences in schooling outcomes for children from the same cluster and even from the same household.

The analysis in this paper proceeds in the following manner. First, we estimate a Heckman Sample Selection Model to account for the sample selection issue in the model. Using this model, first we examine the factors influencing schooling enrolment, and second, conditional on enrolment, we analyse the factors influencing schooling progression. Depending on the econometric issues and the nature of the research questions being addressed we also estimate a few more specialised econometric models to obtain robust coefficients such as a cluster fixed-effects model and household fixed effects models. We estimate a cluster fixed-effects model to account for cluster design of the NFHS survey. Also, in order to address the nature of intra-household gender discrimination in child schooling, that is whether the gender bias that is observed in many previous studies persists within the same household, we estimate household fixed effects models for 15-major states in India. The questions that we address here are: is it the case that in some households, girls are treated differently to boys; or are some households less likely to discriminate than others; if so, is there any regional dimension to this issue? And, finally are the prevailing pattern of gender relations and corresponding regional variations changing over time?

We find strong evidence of a gender bias against female children both at the enrolment stage and also in the number of years in school in the Heckman Sample Selection Model. Interestingly, the result is reversed when we use a Cluster Fixed Effects Model, where inside a cluster, conditional on enrolment a female child is estimated to continue in school for a longer period, relative to a male child.

2. DATA

The dataset used in this paper comes from the second and third round of the nationally representative *Indian National Family Health Surveys (NFHS-2 and 3)*, conducted in 1998-99 and 2005-06.[i] The surveys were conducted by the International Institute for Population Sciences (IIPS), India and funded by the United States Agency for International Development (USAID) through ORC Macro, USA and UNICEF. They were administered on more than 90,000 ever-married women aged 15-49 years and contain detailed information on household structure, labour market participation, asset ownership, health and educational characteristics for all the household members. The datasets are rich, unique, and nationally representative.

The paper focuses on the fifteen major states of India, which represent more than 80 per cent of the Indian population. In the Indian educational system there are five grades within the primary school and five grades within the secondary school followed by two years of higher secondary school, with age six typically considered to be the normal primary school enrolment age. Since late enrolments are a common feature in many rural areas, as in Pal (2004a) we focus on the schooling status of children aged between 10-20 years. According to the descriptive statistics presented in Table 1, there are 59,534 children in the 10-20 year age-group, and of these children 92 per cent are currently enrolled. However, being currently enrolled is an imperfect indicator of whether or not the children are in school. We further look at the number of years of schooling that each school-age child has received contingent on being enrolled. We observe that on average a child has received 6.89 years of schooling. In terms of parental educational attainment, we observe that 28 per cent of fathers have no education, while the figure is considerably higher for mothers with 53 per cent having no schooling.

This paper empirically analyse the demand for child schooling in India. First, we focus on the likelihood of a child's school enrolment and second, conditional on enrolment the number of years the child continues in school. The first dependent variable is a dichotomous variable, indicating whether or not the child was enrolled in a school. The second dependent variable is a continuous variable which takes on the value of the discrete number of years the child continues in school while it is conditional on- enrolled in school equal to 1.

The primary focus of this paper is to examine the factors influencing the schooling outcomes of 10-20 year old children in India, with a specific focus on the nature of gender-bias in schooling outcomes. There are however a number of econometric issues that need to be addressed.

ECONOMETRIC ISSUES

Sample selection bias

As noted in Table 1, approximately 8 per cent of the children in the sample have no education, hence the data has a large number of zeros in the dependent variable 'years of schooling'. Under these circumstances, estimating an OLS-model using 'number of years of schooling' as our dependent variable may result in biased estimates as we do not observe schooling for those children who are not currently enrolled. Given the potential for sample selection bias, we estimate a Heckman Sample Selection model, where, in Stage 1, a probit equation is estimated to examine the probability of a child attending school and in the Stage 2, we estimate the years of schooling, contingent on being enrolled in school. So, the equation of interest is,

$$h_i = \beta x_i + \varepsilon_i. \qquad (1)$$

where, h_i represents the child *i*'s years of schooling and it is a continuous variable, x_i is a vector of explanatory variables and ε_i is a random error term and

the selection equation is,

$$h_{1i}^* = \sigma\, x_{1i} + v_i \qquad [x \subset x_1] \qquad (2)$$

where h_{1i}^* is a latent variable representing the household's desire or preference to enroll a child in school, which can be expressed as a linear function of variables that affect the probability of a child attending school. However, we do not observe h_{1i}^* and instead we observe the dummy variable h_{1i}, which takes the value 1 if the child is enrolled in a school and 0 otherwise.

In other words, h_i is only observed when h_{1i} is 1. A sample selection model allows for a correlation coefficient between the disturbances of the two equations. The explanatory variables included in the analysis are an array of child related variables (such as child's gender, age, indicator variables for birth-order), household socio-economic characteristics (such as the child's caste, wealth status measured using the five wealth quintiles that are available in the dataset), and parental characteristics such as the educational attainment of the mother and father, their age, their employment status, their occupation and a set of maternal autonomy variables since the focus of this study relates to gender differentiated schooling. Finally, we include variables to reflect regional characteristics such as the child's state of residence and whether the child lives in a rural or urban area. A full description of the key explanatory variables used in the analysis is presented in Table 1.

Further for identification purpose, it is difficult to find a variable that significantly influences the enrolment equation but, does not influence the 'years of schooling' equation. The probability of school enrolment and the 'years of schooling' by their very nature are closely linked since they are both outcomes of household decisions influenced by a common set of variables (see Kingdon, 2002). Wooldridge (2002a) argues that the identification of the selection term through the non-linear functional form in Heckman Model is reasonable. We use three variables for identification: an interaction term between mother's occupation and child's gender and two more variables: one indicating mother's involvement in decision-making with regard to large household purchases and other, indicating mother's involvement in decision-making with regard to purchases for daily needs. A series of Likelihood Ratio Tests justify their exclusion in the second-stage estimation of the model.

Unobserved heterogeneity

Our next econometric consideration is the cluster design of the dataset. Households within a cluster might significantly vary on the basis of ethnicity, religion, wealth, occupation and educational status, yet there might be some neighbourhood effects and correlation between them. There will typically be more homogeneity within clusters than between clusters (Dancer and Rammohan, 2007; Deaton, 2000). However, it is not always possible to observe all the common characteristics shared by the households within a cluster, and ignoring some of those unobserved heterogeneity in the regression model would result in omitted variable bias in the estimated coefficients. This is particularly true in studies on demand for child schooling in developing countries, where the data rarely contains any information on supply side community characteristics such as proximity and availability of schools, and quality of schools. For this purpose, the use of cluster fixed-effects estimation model is used to control for all of the common unobserved characteristics shared by children from the same cluster. Consequently, estimation of within cluster models will account for any individual, household and community level heterogeneity within the cluster. In order to account for the cluster design of data in the NFHS-3, and also in an attempt to control for the cluster specific variations such as availability and quality of schools, this study has also estimated a cluster fixed effects model in two different steps. Each cluster in the data represents a PSU and there are a total of 2758 clusters. The households in a single cluster live close by, they are not randomly distributed over space rather they are geographically grouped. Furthermore, the data has no information on community characteristics such as the proximity and availability of schools, and quality of schools for urban households. To address this potential problem of unobserved heterogeneity, we have estimated a cluster fixed effects model to account for the presence of any intra-cluster variation.

In the first step a standard probit model is estimated to address the selection bias in the model, and in the second step a cluster fixed effects model is estimated including the *inverse mills ratio* from the probit model.

The Cluster fixed-effects model also corrects for the selection bias. Accordingly, in the first stage, a standard probit regression is estimated to examine the probability that, a child in the household is enrolled in school. Including the *Inverse Mills Ratio* obtained from this first stage probit regression, a cluster fixed effects regression model with unbalanced clusters is estimated in the second stage. Here, the equation of interest is

$$h_{ij}= \beta x_{ij} + b_j+ \varepsilon_{ij.} \qquad (3)$$

where, h_{ij} represents the years of schooling for the child i in cluster j and it is a continuous variable; b_j represents the cluster specific unobserved effect. In using a fixed-effects model, the goal is to eliminate b_j because it is assumed to be correlated with one or more of the x_{ij}. However, it is not appropriate to estimate this equation directly. Instead in the first stage the selection equation is,

$$h_{1ij}^* = \sigma\, x_{1ij} + \upsilon_{ij} \qquad [x_{ij} \subset x_{1ij}] \qquad (4)$$

h_{1ij}^* is a latent variable representing the household desire or preference to enroll a child in school, which can be expressed as a linear function of variables that affect the probability of a child attending school. However, we do not observe h_{1ij}^* and instead we observe the dummy variable h_{1ij}, which takes the value 1 if the child is enrolled in a school and there are at least 2 children per cluster present in the sample, and 0 otherwise. Hence,

$$h_{1ij} = 1 \quad \text{iff } h_{1ij}^* > 0$$

$$h_{1ij} = 0 \quad \text{iff } h_{1ij}^* \leq 0 \qquad (5)$$

and h_{ij} is observed when h_{1ij} is 1.

Household Fixed Effects

Finally, in order to address the nature of intra-household gender discrimination in child schooling, that is whether the gender bias that is observed in many previous studies persists within the same household, we estimate household fixed effects models for different states in India. We analyse the extent of regional contradictions in gender relations in the intra-household resource allocation for child schooling.

Specifically, there are three important factors that need to be addressed. First, as there is likely to be more than one child per household in the sample, we need to consider the corresponding correlation between the error terms of the siblings' equations in the model. Second, the decision on the level of schooling investment of an individual child is always undertaken at the household level, hence we need to acknowledge the presence of household level unobserved heterogeneity in the model for example household preferences, endowments, resource levels etc., which is likely to result in omitted variable bias. Third, it is also quite important to analyse differential allocation of schooling resources in a household based on the child's gender. It is therefore appropriate to treat the household as a cross-section observation unit rather than focusing on the individual child (Wooldridge, 2002a). An estimation of household fixed effects model helps to overcome the household specific correlation between the children. It also controls the household level unobserved heterogeneity in the model and investigates for the presence of any possible gender discrimination in the intrahousehold resource allocation.

Estimating a fixed effects model with a cross-sectional database is not a usual practice, yet in demography, it is more commonly used on siblings or matched pair samples to control for unobserved household and background characteristics. We treat each household as a cluster and only those explanatory variables, that vary within households such as the individual child's characteristics are included in the model (Aslam and Kingdon, 2006; Kingdon, 2005). In the dataset the cluster sizes are not the same, owing to the fact that, number of children from one household are not the same as that from another, e.g. they vary between 2-11. For this purpose, the paper adopts the household fixed effects model with unbalanced clusters.

Similar to the cluster fixed-effects model the household fixed effects model for each state is also estimated in two different steps to correct the sample selection bias. In the first stage, a standard probit regression is estimated and a household fixed effects regression model is estimated in the second stage.[ii] However, in such analysis it is not possible to successfully infer about the intrahousehold allocation of schooling resources at the initial enrolment stage, when the household is faced with a decision to enrol a child in the school. We can only successfully infer about the nature of the allocation of schooling resources between the children within a household once they are enrolled in school.

3. Estimation Results

The main results of this analysis are presented in Tables 2, 3 and 4. However, this paper discusses the Heckman Sample Selection Model and Cluster fixed-effects model results for 2005-06 dataset only. In Table 2, columns [1] and [2] present the estimates from the Heckman model and in Columns [3] and [4] present the results for Cluster fixed-effects. We present Marginal effects for the 1st stage Probit estimates and the coefficients for the OLS estimates.

The first point to note (in the Heckman model results) is the statistical significance of rho, the correlation coefficient which points to the presence of a selection bias if we estimate a child's years of schooling ignoring the sample selection bias.

Our results in columns [1] and [2] indicate that the gender of the child matters in the decision to enrol in school and once enrolled, in the decision to continue in school. In other words, being a male child raises the probability of being enrolled in a school by 2.7 percentage points. In the second stage estimates, the dummy variable for male is statistically significant and positively correlated with years of schooling as well.

The variables representing the child's birth order are statistically significant at the one per cent level in both the stages of schooling. In other words, later born children (i.e higher birth-order children) have significantly lower schooling years relative to a first-born child. The economic impact of these variables are however negligible, as the marginal effects in the first stage enrolment equation are small in magnitude. Nevertheless, the empirical literature on birth order effects in developing countries is ambiguous (Rammohan and Dancer, 2008; and Parish and Willis, 1994; Behrman and Taubman, 1986).

In this sample there is strong evidence of significant resource constraints on the likelihood of a child's schooling enrolment and contingent on that on child's years of schooling. More specifically, the household-specific demographic variables that are used as proxies for household resources, such as the household size, proportion of daughters in the family along with parental schooling and labour market status are found to be statistically significant in influencing child schooling outcomes. The results show that, household size is statistically significant and negatively correlated with both schooling enrolment and also years of schooling (also see Glick and Sahn, 2000; Patrinos and Psacharopoulos, 1997). The variable proportion of daughters in the household is statistically significant and positively signed. This is consistent with previous research that has shown that an increase in the proportion of daughters in the household is positively correlated with better schooling and health outcomes for children (see Garg and Morduch, 1998; Parish and Willis, 1994).

As expected parental education is statistically significant and positively signed with both schooling enrolment and years of schooling of children in this model. It is evident that relative to the base category of no schooling, all levels of parental schooling - are statistically significant and are positively correlated with both the likelihood of enrolment in school and also, the number of years continuing in school. So having a father with primary school education increases the likelihood of a child being enrolled in school by 1.8 percentage points, relative to a child whose father has no education. Similarly having a primary school educated father also increases child schooling by 0.15 years, relative to a child whose father has no schooling. Having a secondary-school educated father has an even larger influence on schooling outcomes. In terms of mother's schooling, a child with a primary school educated mother is estimated to continue 0.29 more years in school relative to a child with uneducated mother. This is almost twice as large as that of a child with a primary school educated father. These results suggest that lower levels of mother's schooling are more influential than lower levels of father's education in improving schooling outcomes. At higher levels of parental schooling however, father's education is more influential.

Similarly, father's occupational status is also statistically significant for child schooling only in the second stage years of schooling equation. However, compared to the base category of children whose fathers do not work, the children whose fathers are employed in professional, clerical and sales are estimated to continue for 0.38 more years in school. Similarly, children whose fathers are employed in agriculture and self-employed are estimated to continue only 0.26 additional years in school. However, mother's employment status has the opposite effect. Mother's employment in service sector or even in manual jobs has a negative influence on child's schooling outcomes. This is possibly a unique feature for predominantly rural Indian datasets (also see Behrman *et al.*, 1999). In Indian villages a working mother in the household predominantly reflects poor economic status of the household and in such cases the mother is mostly employed as a casual labourer.

Along with the schooling and labour market status of the mother, the variables representing mother's self-reported economic and social autonomy in the household, also have statistically significant positive influence on child schooling. These variables are a measure of the mothers' participation in household decision making, their freedom of movement and independent access to money. For example 'if the mother has a bank or savings account or 'if she is involved in the decision making of household purchases or 'if she has access to mass media (newspaper/television/radio) then the child is more likely to enrol in a school and also continues more years in school.

Not surprisingly, an increase in household wealth significantly increases the probability of a child being enrolled in school, and also the child's estimated years in school.

In India, the role of religion and caste in influencing the schooling outcomes of children is well-established in the literature (Borooah and Iyer, 2005; Drèze and Kingdon, 2001). Our analysis also finds religion to have a statistically significant influence on child schooling, at one per cent level. For example, a child from a Hindu household is 2.7 per cent more likely to enrol in a school and, is also estimated to continue in school for 0.39 additional years, relative to a child from a non-Hindu household. Conversely, children from caste categories such as Scheduled Caste, Scheduled Tribe and Other Backward Classes are significantly disadvantaged not only at the enrolment stage, but also in the number of years that they are at school relative to children from upper castes. In particular, a child from a scheduled tribe community is estimated to have 1.7 per cent lower likelihood of being enrolled in school and if enrolled is expected to have 0.29 fewer years in school relative to a non- scheduled tribe child.

Finally, as expected there are significant regional variations in schooling outcomes across different states in India which has shown very little variation over time.

As with the Heckman sample selection model, the decision to estimate the Cluster fixed-effects model in two different stages is supported by a statistically significant *Inverse Mills Ratio*. Further, a Hausman test justifies that, the fixed effects estimation of the model is preferable over the random effects estimation of the model.

In the cluster fixed-effects model we are able to analyse the factors that influence a child's years of schooling contingent on the fact that the child has already enrolled in a school. It is not possible to successfully infer about what happens in the initial enrolment stage, such as access to school with cluster fixed effects.[iii] So, the first stage standard probit estimates in [3] of Tables 2 are expected to be the same as the first-stage probit estimates of the Heckman model without the cluster fixed effects.

The cluster fixed effects model results are consistent with the findings from the Heckman model and further re-establish our analysis. However, the variable child's gender, albeit statistically significant, is negatively signed. What this means is that inside a cluster, contingent on enrolment in a school, a girl child is estimated to continue more years in school compared to a boy. This is notably a significant outcome for Indian data providing that the similar pattern is observed over time (both in 1998-99 and 2005-06). So, once we clear for the cluster level unobserved heterogeneity in the models there is in fact a pro-female bias in child schooling outcomes within villages in India.

Household Fixed Effects Model

The state level household fixed effects models results are presented in Table 3 and 4 for 1998-99 and 2005-06 respectively. Considering the fact that there is fairly strong evidence of regional variations in gender relations across Indian states (Azam and Kingdon, 2011; Zimmermann, 2011; Kingdon, 2005; Filmer, 2000), one major aspect of this study is to bring out the regional pattern of gender disparities in the intrahousehold allocation of resources for child schooling in the country. For this purpose Household Fixed Effects Models have been estimated and analysed separately for the 15-major states of India. However, as previously mentioned with such kind of analysis, we can only analyse the intrahousehold allocation of schooling resources among the children if they are enrolled in school.

The estimates of the household fixed effects models in Table 3 indicate that gender is a statistically significant variable in only seven states including Andhra Pradesh and Kerala in south India, Punjab and Haryana in north India, Gujarat in western India and West Bengal and Bihar in eastern India. So in these states there is significant gender bias in the intrahousehold allocation of schooling resources. Specifically in the states of Haryana, Gujarat, West Bengal and Bihar, there is statistically significant pro-male bias in the intrahousehold allocation of resources for schooling. More surprising is the negative and statistically significant coefficient for gender in the states of Andhra Pradesh and Punjab along with Kerala, which suggests that, the female children are favoured over the males in the household allocation of schooling resources as they are estimated to spend respectively 0.337, 0.144 and 0.364 additional years in school. Kerala the southernmost state of India has historically been acknowledged for maintaining high human development indicators and even reversing the pro-male bias that is in par with some of the developed countries. On the contrary, while this is not the case with Andhra Pradesh, the state of Punjab reflects an overall grim picture in gender related development indicators (Government of Punjab, 2008)

However, (in Table 3) in states of - Karnataka, Tamil Nadu, Himachal Pradesh, Maharashtra, Rajasthan, Uttar Pradesh, Madhya Pradesh and Orissa there is no statistically significant gender discrimination in the intrahousehold resource allocation for schooling. Though, with this kind of analysis, it is not sufficient to conclude that this is the regional trend of gender relations in intrahousehold resource allocation for child schooling in India since we do not know the nature of intrahousehold resource allocation for schooling at the initial enrolment stage.

Table 4 (for 2005-06) reveals gender is statistically significant in nine states including Andhra Pradesh and Kerala in south India, Punjab and Haryana in north India, Gujarat in western India and West Bengal and Bihar in eastern India. In these states there is significant gender bias in the intrahousehold allocation of schooling resources. Specifically in the states of Rajasthan, Haryana, Gujarat, Orissa, Bihar, Uttar Pradesh and Madhya Pradesh there is statistically significant pro-male bias. Again surprisingly consistent is the pro-female bias in the state of Punjab along with Kerala.

However, comparison between 1998-99 and 2005-06 models in Table 3 and 4 reveal, gender bias is no longer statistically significant in West Bengal. Rather disturbing is the statistically significant gender bias in the states of Rajasthan, Orissa, Uttar Pradesh and Madhya Pradesh. These states were not among the list of states exhibiting statistically significant gender bias in 1998-99 (Table 3). Equally disturbing are the persistent gender bias observed in Gujarat and Haryana along with a poor state like Bihar (both in 1998-99 and 2005-06).

In the states of – Kerala, Andhra Pradesh, Karnataka, Tamil Nadu, Maharashtra, Himachal Pradesh and Punjab there is no statistically significant pro-male gender discrimination in the intrahousehold resource allocation for schooling. This study finds no clear-cut contrast between north-India and south-India in the regional pattern of gender relations in the intrahousehold resource allocation for child schooling. Of course, there is a clear trend that south India is performing well in gender relations, there is no such clear trend evident in any other parts of India.

Apart from gender, other individual characteristics of the child such as age and birth order in the family also demonstrate considerable variations across states in influencing the intrahousehold resource allocation for child schooling.

4. Conclusions

One of the key contributions of this paper is in unravelling the role of gender in influencing child schooling in India. The paper finds strong evidence of a gender bias against female children both at the enrolment stage and also in the number of years in school in the Heckman Sample Selection Model. Interestingly, the results are reversed when we use a Cluster Fixed Effects Model, where inside a cluster, conditional on enrolment a female child is estimated to continue for a longer period in school relative to a male child.

Other variables such as household wealth and parental education have the expected signs, indicating the role of resource constraints in influencing child schooling outcomes. Finally the analysis finds that there are also significant regional variations in child schooling outcomes and factors such as religion and caste are significant determinants for child schooling in India.

Finally we find no clear-cut contrast between north-India and south-India in terms of gender differences in the intrahousehold resource allocation for child schooling. Of course, there is a clear trend that south India is performing well in gender relations, there is no such clear trend evident in any other parts of India

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APPENDIX

TABLE 1: DESCRIPTIVE STATISTICS

Variables	Full Sample Mean (N=59534)
Child’s school attendance(enrolled in a school =1)	0.92
Child's years of schooling (corrected for enrolled in school=1)	6.89
Gender (1 if male)	0.53
Age (in years)	14.19
Age squared	
Birth order 1 (1 if 1st born, 0 otherwise)	0.30
Birth order 2 (1 if 2nd born, 0 otherwise)	0.27
Birth order 3 (1 if the 3rd born, 0 otherwise)	0.19
Birth order 4 (1 if the 4th born, 0 otherwise)	0.11
Birth order 5 (1 if the 5th born, 0 otherwise)	0.12
Father's age	43.18
Father’s education : no-schooling	0.28
Father’s education : primary-schooling	0.18
Father’s education: secondary-school	0.43
Father’s education: higher secondary	0.11
Father’s occupation: unemployed	0.02
Father’s occupation: professionals, clerical & sales	0.26
Father’s occupation: agriculture-self employed	0.29
Father’s occupation: services	0.06
Father’s occupation: manual labour	0.37
Mother's age	37.17
Mother’s education: no-schooling	0.53
Mother’s education: primary-school	0.16

Variables	Full Sample Mean (N=59534)
Mother's education: secondary-school	0.26
Mother's education: higher secondary	0.05
Mother's occupation: unemployed	0.53
Mother's occupation: professionals, clerical & sales	0.05
Mother's occupation: agriculture	0.27
Mother's occupation: services	0.05
Mother's occupation: manual labour	0.10
Mother's health care status: 1 if mother decides on her own/involved in the decision on her health care	0.69
Mother's economic status: 1 if the mother decides/involved in decisions on large house hold purchases	0.64
Mother's economic status: 1 if the mother decides/involved in decisions on household purchases for daily needs	0.72
Mother's economic status:1 if the mother has bank or savings account	0.18
Mother's social status: 1 if the mother needs permission for visits to family/relatives	0.30
Mother's access to mass media: 1 if the mother reads newspaper or listens radio or watches TV everyday/at least once a week	0.63
Household Characteristics	
Household size (number of household members)	6.25
Daughters as a proportion of children in the household	0.47
Wealth quintile 1: Poorest	0.15
Wealth quintile 2: Poor	0.16
Wealth quintile 3: Middle	0.19
Wealth quintile 4: Rich	0.24
Wealth quintile 5: Richest	0.27
Community Characteristics	
Religion- Hindu	0.79
Schedule Caste	0.20

Variables	Full Sample Mean (N=59534)
Schedule Tribe	0.07
Other Backward Classes	0.40
Upper caste or no caste	0.33

TABLE 2: ESTIMATES OF THE SAMPLE SELECTION MODEL WITH/WITHOUT CLUSTER FIXED EFFECTS.

Variables	Heckman Selection Model (Full Maximum Likelihood Estimation)		Sample Selection Model with Cluster Fixed Effects	
	1st stage Probit (N=59534)	2nd stage MLE Estimates: (N=54913)	1st stage Probit (N=59534)	2nd stage Fixed Effects Estimates (N=54909)
Male	0.027*** (0.000)	0.071** (0.036)	0.028*** (0.002)	-0.209*** (0.029)
Age	0.004*** (0.002)	1.809*** (0.060)	0.005*** (0.002)	1.750*** (0.027)
Age squared	0.000*** (0.000)	-0.040*** (0.002)	0.000*** (0.000)	-0.037*** (0.001)
Birth order 2	0.000 (0.002)	-0.114 (0.115)	0.000 (0.001)	-0.136*** (0.019)
Birth order 3	0.000 (0.001)	-0.187* (0.106)	0.000 (0.002)	-0.216*** (0.024)
Birth order 4	-0.003* (0.002)	-0.217** (0.103)	-0.003 (0.002)	-0.203*** (0.031)
Birth order 5 and above	-0.007*** (0.002)	-0.266*** (0.093)	-0.007*** (0.002)	-0.161*** (0.036)
Parental Characteristics				
Father's age	0.000*** (0.000)	0.004 (0.003)	0.000** (0.000)	0.004** (0.002)
Father’s edu: primary	0.018*** (0.001)	0.150*** (0.023)	0.019*** (0.001)	-0.329*** (0.032)
Father’s edu: secondary-	0.034*** (0.002)	0.565*** (0.027)	0.035*** (0.002)	-0.066** (0.031)
Father’s edu: higher than seco	0.025*** (0.001)	0.897*** (0.050)	0.026*** (0.001)	0.194*** (0.041)
Father’s occ: Prof/clerical/sales	0.006 (0.004)	0.377*** (0.116)	0.007* (0.004)	0.249*** (0.067)
Father’s occ: agriculture-self employed	0.003 (0.004)	0.256** (0.111)	0.003 (0.003)	0.161** (0.065)

Variables	Heckman Selection Model (Full Maximum Likelihood Estimation)		Sample Selection Model with Cluster Fixed Effects	
	1st stage Probit (N=59534)	2nd stage MLE Estimates: (N=54913)	1st stage Probit (N=59534)	2nd stage Fixed Effects Estimates (N=54909)
Father's occ: services	0.003 (0.003)	0.220** (0.111)	0.003 (0.004)	0.152** (0.069)
Father's occu: manual	0.004 (0.003)	0.270*** (0.104)	0.005 (0.003)	0.196*** (0.066)
Father's occ prof * male	-0.011** (0.006)	-0.186 (0.042)	-0.012*** (0.004)	-0.022 (0.038)
Father's occ manual* male	-0.006*** (0.002)	-0.165*** (0.045)	-0.007*** (0.003)	-0.094*** (0.036)
Mother's age	0.000 (0.000)	0.016*** (0.003)	0.000 (0.000)	0.020*** (0.003)
Mother's edu:prim	0.021*** (0.001)	0.293*** (0.018)	0.021*** (0.001)	0.003 (0.026)
Mother's edu: secon	0.026*** (0.001)	0.549*** (0.020)	0.026*** (0.002)	0.286*** (0.025)
Mother's edu: higher than seco	0.010*** (0.003)	0.468*** (0.073)	0.008 (0.005)	0.211*** (0.045)
Mother's occu:prof	0.002 (0.003)	-0.053 (0.070)	0.001 (0.004)	-0.032 (0.046)
Mother's occ: agr	0.001 (0.001)	-0.019 (0.026)	0.002 (0.001)	-0.078*** (0.027)
Mother's occ services	-0.006*** (0.002)	-0.416 (0.036)	-0.006** (0.003)	-0.307*** (0.041)
Mother's occ: manual	-0.006*** (0.002)	-0.125*** (0.022)	-0.006** (0.003)	-0.097*** (0.030)
Mother's occu. Prof* male	-0.012 (0.008)	-0.169** (0.078)	-0.010 (0.009)	-0.076 (0.061)
Mother's occ. manual* male	0.006*** (0.001)		0.007** (0.003)	

Variables	Heckman Selection Model (Full Maximum Likelihood Estimation)		Sample Selection Model with Cluster Fixed Effects	
	1st stage Probit (N=59534)	2nd stage MLE Estimates: (N=54913)	1st stage Probit (N=59534)	2nd stage Fixed Effects Estimates (N=54909)
Mother involved in health care decisions	-0.002** (0.001)	-0.024** (0.011)	-0.002 (0.001)	-0.018 (0.021)
Mother involved in the decisions on large purchases	-0.002* (0.001)		-0.003** (0.001)	0.051** (0.021)
Mother involved in purchases for daily needs	0.002** (0.001)		0.003* (0.001)	-0.027 (0.022)
Mother has bank/savings account	0.010*** (0.001)	0.134*** (0.016)	0.010*** (0.002)	0.037** (0.020)
Mother needs permission to visit family/relatives	-0.002 (0.001)	-0.005 (0.017)	-0.002 (0.001)	-0.009 (0.022)
Mother has access to mass media	0.008*** (0.001)	0.089*** (0.021)	0.009*** (0.001)	-0.038* (0.022)
Household size	-0.001*** (0.000)	-0.032*** (0.005)	-0.001*** (0.000)	-0.012*** (0.003)
Proportion of daughters in the hh	0.009** (0.004)	0.121*** (0.042)	0.009*** (0.002)	0.000 (0.033)
wealth quintile: Poor	0.013*** (0.001)	0.280*** (0.029)	0.014*** (0.001)	-0.065* (0.037)
Wealth quintile: Medium	0.022*** (0.001)	0.442*** (0.039)	0.022*** (0.001)	-0.080** (0.042)
Wealth quintile: Rich	0.032*** (0.001)	0.760*** (0.060)	0.033*** (0.002)	0.171*** (0.046)
Wealth quintile: Richest	0.041*** (0.002)	1.195*** (0.076)	0.042*** (0.002)	0.548*** (0.052)
Religion: Hindu	0.027*** (0.003)	0.388*** (0.054)	0.028*** (0.002)	0.018 (0.029)
Schedule Caste	0.002 (0.001)	-0.120***	0.002 (0.002)	-0.160*** (0.027)

Variables	Heckman Selection Model (Full Maximum Likelihood Estimation)		Sample Selection Model with Cluster Fixed Effects	
	1st stage Probit (N=59534)	2nd stage MLE Estimates: (N=54913)	1st stage Probit (N=59534)	2nd stage Fixed Effects Estimates (N=54909)
Schedule Tribe	-0.017*** (0.005)	-0.286*** (0.029)	-0.018*** (0.003)	-0.142*** (0.050)
Other Backward Classes	-0.001 (0.001)	-0.103*** (0.032)	-0.001 (0.001)	-0.082*** (0.022)
Urban residence	-0.015*** (0.002)	-0.202*** (0.032)	-0.016*** (0.002)	
State dummies	Yes	Yes	Yes	Yes
_cons		-12.786*** (0.396)		-10.545*** (0.220)
mills				-3.766*** (0.136)
Rho		-0.201*** (0.025)	0.178	
Pseudo R^2			0.2885	
R^2 -within -between -overall				0.6119 0.7386 0.6384

Note: *** indicates significant at 1 per cent level,
** indicates significant at 5 per cent level,
* indicates significant at 10 per cent level.

Source: International Institute for Population Sciences (IIPS) and Macro International (2007) *National Family Health Survey (NFHS-3), 2005-06: India*, Mumbai: IIPS.

TABLE 3: ESTIMATES OF THE HOUSEHOLD FIXED EFFECTS REGRESSION MODELS INDEPENDENTLY FOR 15 MAJOR STATES OF INDIA IN 1998-99.

States	Child's Characteristics within a Household					
	Age	Gender	Birth order-2	Birth order- 3	Birth order- 4	Birth order- 5 and more
	Coef.(SE)	Coef.(SE)	Coef.(SE)	Coef.(SE)	Coef.(SE)	Coef.(SE)
Andhra Pradesh	-0.100 (0.415)	-0.337** (0.169)	-2.080*** (0.324)	-2.398*** (0.403)	-2.523*** (0.521)	-2.929*** (0.630)
Karnataka	1.999*** (0.161)	0.147 (0.089)	-0.401*** (0.123)	-0.332 (0.214)	-0.152 (0.314)	0.436 (0.449)
Kerala	2.544*** (0.145)	-0.364*** (0.082)	-0.339*** (0.123)	-0.366 (0.229)	-0.157 (0.364)	0.693 (0.503)
Tamil Nadu	1.456*** (0.157)	0.046 (0.083)	-0.690*** (0.131)	-1.070*** (0.236)	-1.151*** (0.353)	-1.135** (0.512)
Punjab	1.806*** (0.145)	-0.144* (0.078)	-0.228** (0.118)	-0.325 (0.203)	-0.187 (0.291)	-0.146 (0.429)
Haryana	1.676*** (0.131)	0.303*** (0.080)	-0.388*** (0.117)	-0.723*** (0.203)	-0.684** (0.294)	-0.818** (0.398)
Rajasthan	0.817*** (0.155)	-0.173 (0.178)	-1.209*** (0.163)	-1.432*** (0.210)	-1.671*** (0.253)	-1.985*** (0.325)
Himachal Pradesh	1.465*** (0.134)	-0.052 (0.072)	-0.465*** (0.119)	-1.077*** (0.220)	-1.448*** (0.314)	-1.363*** (0.432)
Maharashtra	1.526*** (0.114)	0.023 (0.061)	-0.498*** (0.091)	-0.835*** (0.155)	-0.884*** (0.231)	-0.786** (0.319)
Gujarat	1.526*** (0.144)	0.365*** (0.082)	-0.316*** (0.116)	-0.480** (0.199)	-0.336 (0.281)	-0.598 (0.377)
West Bengal	1.363*** (0.168)	0.454*** (0.097)	-0.439*** (0.147)	-0.716*** (0.253)	-0.501 (0.366)	-0.554 (0.497)
Bihar	1.487*** (0.115)	0.534*** (0.077)	-0.356*** (0.099)	-0.592*** (0.155)	-0.879*** (0.205)	-0.816*** (0.277)
Orissa	1.118*** (0.219)	0.119 (0.109)	-1.074*** (0.240)	-1.219*** (0.291)	-1.251*** (0.363)	-1.390*** (0.462)
Uttar Pradesh	0.890*** (0.141)	-0.003 (0.134)	-1.091*** (0.172)	-1.407*** (0.200)	-1.720*** (0.235)	-1.949*** (0.285)
Madhya Pradesh	0.834*** (0.190)	0.008 (0.146)	-0.850*** (0.243)	- 1.1.235*** (0.291)	-1.447*** (0.314)	-1.436*** (0.351)

Note: *** indicates significant at 1 per cent level,
** indicates significant at 5 per cent level,
* indicates significant at 10 per cent level.

Source: International Institute for Population Sciences (IIPS) and ORC Macro (2000) *National Family Health Survey (NFHS-2), 1998-99: India*, Mumbai: IIPS.

TABLE 4: ESTIMATES OF THE HOUSEHOLD FIXED EFFECTS REGRESSION MODELS INDEPENDENTLY FOR 15 MAJOR STATES OF INDIA IN 2005-06.

States	Child's Characteristics within a Household					
	Age	**Gender**	**Birth-order-2**	**Birth-order- 3**	**Birth-order- 4**	**Birth-order-5 and more**
Andhra Pradesh	1.630*** (0.130)	-0.077 (0.146)	-0.516*** (0.103)	-0.785*** (0.182)	-0.945*** (0.265)	-1.272*** (0.354)
Karnataka	2.055*** (0.144)	0.046 (0.108)	-0.395*** (0.133)	-0.292 (0.225)	-0.271 (0.340)	0.063 (0.452)
Kerala	2.183*** (0.174)	-0.417** (0.201)	-0.455*** (0.139)	-0.589** (0.273)	-0.626 (0.451)	0.219 (0.683)
Tamil Nadu	1.644*** (0.156)	-0.161 (0.137)	-0.312*** (0.127)	-0.457** (0.230)	-0.159 (0.341)	-0.275 (0.499)
Punjab	1.375*** (0.150)	-0.308** (0.138)	-0.494*** (0.118)	-0.712*** (0.197)	-0.816*** (0.288)	-0.331 (0.428)
Haryana	1.813*** (0.176)	0.372** (0.147)	-0.476*** (0.142)	-0.771*** (0.245)	-0.720** (0.371)	-0.606 (0.519)
Rajasthan	1.524*** (0.137)	0.630*** (0.125)	-0.361*** (0.127)	-0.655*** (0.200)	-0.690** (0.283)	-0.583 (0.402)
Himachal Pradesh	1.595*** (0.146)	0.134 (0.122)	-0.453*** (0.110)	-0.633*** (0.207)	-0.738** (0.347)	-0.414 (0.489)
Maharashtra	2.369*** (0.185)	-0.102 (0.087)	-0.066 (0.147)	-0.333** (0.164)	-0.451** (0.212)	-0.130 (0.273)
Gujarat	1.990*** (0.157)	0.464*** (0.142)	-0.447*** (0.129)	-0.443** (0.226)	-0.467 (0.317)	-0.359 (0.460)
West Bengal	1.398*** (0.155)	0.260 (0.163)	-0.622*** (0.126)	-0.796*** (0.220)	-0.475 (0.298)	-0.144 (0.420)
Bihar	1.733*** (0.122)	0.815*** (0.153)	-0.332*** (0.105)	-0.770*** (0.171)	-0.776*** (0.244)	-0.889*** (0.330)
Orissa	1.821*** (0.164)	0.383*** (0.140)	-0.758*** (0.149)	-1.151*** (0.254)	-1.016*** (0.388)	-1.035** (0.517)
Uttar Pradesh	1.741***	0.233***	-	-0.899***	-1.041***	-1.075***

States	Child's Characteristics within a Household					
	Age	**Gender**	**Birth-order-2**	**Birth-order- 3**	**Birth-order- 4**	**Birth-order-5 and more**
	(0.069)	(0.067)	0.549*** (0.058)	(0.094)	(0.130)	(0.177)
Madhya Pradesh	1.633*** (0.091)	0.246*** (0.090)	-0.501*** (0.081)	-0.800*** (0.131)	-0.830*** (0.184)	-0.751*** (0.249)

Note: *** indicates significant at 1 per cent level,
** indicates significant at 5 per cent level,
* indicates significant at 10 per cent level.

Source: International Institute for Population Sciences (IIPS) and Macro International (2007) *National Family Health Survey (NFHS-3), 2005-06: India*, Mumbai: IIPS.

End Notes:

[i] This study uses both the second and third round of the nationally representative *Indian National Family Health Surveys (NFHS-2 and 3)*, conducted in 1998-99 and 2005-06. However, due to the specific formatting requirement of the journal to maintain word limitations we are only able to present the 2005-06 estimates for both the Heckman Sample Selection Model and Cluster fixed-effects model. The results for 1998-99 are available upon request. The estimates for Household fixed effects models for 15 major states are presented for both the time periods to highlight the variation over time.

[ii] At this stage it is not appropriate to estimate a fixed effect probit regression to deal with the sample selection bias, instead we estimated a standard probit regression (Wooldridge, 2002b).

[iii] Same as [ii]