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Demand or supply for schooling in rural India?

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Abstract

Is the poor human capital investment of rural Indian families primarily a supply side or a demand side issue? Can time use data help analyze some of the hidden dimensions of development? We examine school attendance and total human capital investment time (time in school plus travel time plus in-home instructional time) using the Indian Time Use Survey of 1998-1999 and the 7th All India School Education Survey (AISES). Probit and sample selection bias regression estimates indicate that the influence of supply side factors (school quality and availability) is large relative to the impact of household characteristics (e.g. low income). We discuss the policy implications and illustrate the advantages of time use data in analysis of development.

JEL-Codes: I2, I24, I25, O15

Keywords: Schooling, human capital accumulation, rural India

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1 Introduction

The crucial role of human capital makes it all the more essential to pay attention to the close relation between sensible public action and economic progress, since public policy has much to contribute to the expansion of education and the promotion of skill formation. The role of wide-spread basic education in those countries with successful growth-mediated progress cannot be overemphasized “(Dreze and Sen, 2002)”.

The value of education for development is increasingly recognised – both in the instrumental sense of enabling rapid growth in GDP and in the direct attainment of human self-consciousness and capability. India has been one of the fastest growing economies in the world today, but within India, and particularly within rural India, the distribution of educational opportunities and attainment is highly unequal. Schools in tents or outdoors, or with absentee teachers, coexist with schools whose teachers and resources are “world class” in quality and there is substantial variation across regions in the average level, and in the inequality in quality in local schools.[1]

Although no individual family can decide the nature of their local school system, those systems are (at least partly) the product of a collective choice, which acts as a constraint on individual choices. However, given the educational alternatives available to them in their local area, individual families may make very different decisions regarding their children’s schooling – choices which will have enormous implications for their children’s lives. This paper therefore asks: How much of the inequality in human capital investment in rural India can be explained by the supply side (i.e. variation in the availability and quality of locally available schooling), and how much can be attributed to the demand side (i.e. variation in the attributes and choices of students and households)?

As well as our direct interest in the substantive issue of school attendance, one of the purposes of this paper is methodological. We use two sources of data – the Indian Time Use Survey (ITUS) and the All India School Education Survey (AISES), and we match these two sources at the state level. The former provides data on time spent by children on human capital accumulation, and the latter provides indicators of school quality and availability. Our perspective is that some crucial aspects of the development process (e.g. human capital investment, social capital formation, environmental degradation)[2] largely occur outside the market economy and involve decisions about time allocation within households. In general, the data on market incomes and financial flows of households which economists usually analyze cannot reveal much about in-

[1] The literature on education in India is voluminous and we do not attempt to survey it here. Some important references are PROBE (1999); Dreze and Sen (2002) and the references therein.

[2] In a previous paper (Motiram and Osberg 2010a), we have used the ITUS to assess the relative importance of ‘bridging’ and ‘bonding’ social capital for access to drinking water. In future work, we plan to link ITUS data to geo-coded data on deforestation.

dividuals who have little or no money income or expenditure (e.g. children; many women; the very poor). However, every individual has 24 hours of time, every day, so the analysis of time use data can help us understand the lives of people who are often ignored in studies using conventional data. We hope to illustrate the potential advantages of time use data, particularly when merged with other data sources, in analyzing key aspects of the development process.

Analysis of time use data is particularly important in developing countries, where the proportion of poor tends to be high, the informal/unorganized sector employs a substantial proportion of people and the process of development is shifting activities and individuals from the informal economy of the household to the formal market sector. We argue that representative surveys of time use within households can help enormously in measuring the extent of the informal household economy and in understanding its transformation during the structural changes of the development process. We hope that this paper provides an impetus (at least to a certain extent) to the collection and analysis of time use data in developing countries.

Section 2 of the paper begins with a brief description of our data sources – the Indian Time Use Survey of 1998-1999 (ITUS) and the 7th All India School Education Survey of 2002 (AISES) – and presents an overview of school quality, attendance and time spent by children on human capital accumulation in India. Given that the ITUS is the only large representative time use survey available on India our paper is the first to investigate schooling and human capital accumulation using certain unique features of this data. Section 3 then presents probit estimates of the probability of school attendance while Section 4 uses sample selection bias regression techniques to examine the determinants of total human capital investment time (i.e. time spent in school plus travelling to and from school plus homework and in-home instructional time). Section 5 uses these estimates to compare the magnitude, and the inequality, of the human capital investment which is influenced by inequality in access to school facilities, relative to the impact of the social exclusion, low income or low education of Indian families. Section 6 concludes.

2 Description of the data

2.1 The Indian Time Use Survey

The Indian Time Use Survey (ITUS) was conducted by the Central Statistical Organization between June 1998 and July 1999 (for a detailed description of the methodology, see ITUS (1998)). The survey followed a two-stage stratified random sampling design (similar to the one used in the National Sample Surveys (NSS)) to collect information on 18,591 households (12,750 rural and 5,841 urban) with 77,593 persons (53,981 rural and 23,612 urban). To capture seasonal variations in the time use patterns, the survey was conducted in four rounds during the year. A team comprising of two people, one male and the other female, stayed in each village or urban block for nine days and compiled time diaries for normal, abnormal and weekly variant days.[3] Respondent households were first visited to assess their weekly pattern of time use and then revisited to complete a full diary of activities concerning the previous day for all household members over six years of age. The data set contains an individual record of the day's activities of each adult and child over the age of six, a household-level record of household characteristics and an individual-level record of individual characteristics. Although in theory, normal, weekly variant and abnormal days could all be studied separately, since the proportions of abnormal and weekly variant days were found to be negligible,[4] we focus only on normal days in this paper.

The survey was conducted in six states: Haryana, Madhya Pradesh, Gujarat, Orissa, Tamil Nadu and Meghalaya representing northern, central, western, eastern, southern and north-eastern regions, respectively. Although a question can be raised about whether data from six states could fully capture the diversity of India, Hirway (2000:11) has argued that "cross-checking of the results has confirmed that the sample is fairly representative of the country."

One of the advantages of the ITUS is that time use data enables direct examination of whether an individual actually attends an educational institution or not- i.e. we can distinguish between attendance and mere enrolment (as inferred from the principal status of the individual as "student"). As well, we can examine the total time spent by each person in the household on human capital investment, adding up the time spent on attendance, on travel to school and on instruction within the home. The first two components are relevant only for children (who can actually attend school), whereas the third is relevant for both children (as receivers of instruction) and adults (i.e. parents or other elders in the household – as providers of instruction). In a previous paper (Motiram and Osberg, 2010b), we examined instruction within the home by parents. Here, we focus on children and the determinants of their attendance and human capital investment time.

As in our previous paper, we divide children into three age groups: 6-10, 11-14 and 15-18, roughly corresponding to primary, upper primary and secondary/higher-secondary educational levels, respectively.[5] Attendance rates fall off for both boys and girls as children age, reflecting both absenteeism and school dropout. At all ages, the attendance rates for boys are higher than the same for girls, a gender differential that is much greater (and increases more with age) in rural than in urban areas. For all age groups, both for boys and girls, the attendance for Scheduled Castes and Tribes (SC and ST), which are historically disadvantaged groups in the Indian

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3 An "abnormal" day is defined in the "Instruction Manual for Field Staff" ITUS (1998: 23) as "that day of the week when guest arrives, any member of the household suddenly falls sick, any festival occurs, etc.". The "weekly variant" is "determined according to the pattern of the major earners holiday. If the major earner does not holiday, then school children's holiday will be taken. If even this is not applicable, then day of weekly hat (bazaar) may be taken" (ITUS 1998: 23).

4 Hirway (2000:24) noted that: "On an average, of the total 7 days, 6.51 were normal, 0.44 weekly variant day and 0.05 was abnormal day… in rural areas people continue their normal activities on holidays also."

5 Primary stage is from class 1 to class 5, except in Gujarat and Meghalaya, where it is from class 1 to class 4; Upper primary stage is from class 6 to class 8, except in Gujarat (5 to 7), Meghalaya (5 to 7) and Orissa (6 to 7); Secondary and higher secondary stages are from class 9 to class 12 in Haryana, Madhya Pradesh and Tamil Nadu, and from class 8 to 12 in the other states. In all the states, higher secondary stage includes classes 11 and 12. See the AISES publications referred to below.

context, is lower than for others. Female literacy within the household also plays an important role – the presence of a literate female adult (e.g. mother, or an elder sister) at home is strongly positively correlated with attendance for all age groups for both boys and girls.

Our time use data enables us to calculate total human capital investment time for children - i.e. the sum of time spent in school, on travel to school and on work at home. Overall, given their lower rate of school attendance, girls spend on an average less time than boys on human capital investment at all ages – in total, and for each activity (attending school, homework or travelling to school). However, the difference between boys and girls is driven by participation – when we consider girls and boys who spend some time on an educational activity, on the average, they spend similar times at that activity, at all ages.

In analyzing time use data collected using the daily diary method one must recognize that the time devoted to particular activities may vary widely, for the same individual, from day to day and some activities are not necessarily observed every day. Hence, in order to understand the relative importance of particular activities, one must think in an expected value sense, and estimate the probability of episodic activities, and the expected value of time spent in each activity.

Fortunately, in doing such estimation, one is not necessarily limited to the variables in the original time use survey data set. The fact that the location of each respondent is known enables researchers to combine datasets using their geographic codes. In the merged data set, each individual respondent's record combines the time use survey's data on individual daily time use with variables, drawn from other data sources, measuring characteristics of the area in which they live. This enables the researcher to assess the influence that local area characteristics may have on the time use of respondents in that area. We employ this technique in this paper, as we have in others (e.g. in Motiram and Osberg (2010a), where the relevant characteristic of the local area is the availability of groundwater per capita at the district level).

2.2 The Seventh All India School Education Survey

Because the state that each respondent lives in is recorded in the ITUS micro-data, each respondent household in the ITUS can be exactly matched, using the geo-code for each state, to state level data from the Seventh All India School Education Survey (AISES). The AISES collected comprehensive data on a census basis on every facet of school education in India, as of September 30, 2002, e.g. the availability of schooling facilities in rural habitations, physical and educational facilities in schools, enrolment, teachers and their academic and professional qualifications etc. Some of this data, at the national and state level, is available in published reports, and we present some indicators for major states in Table 1.

We can observe from Table 1, which includes both public and private schools, that within India, there is remarkable variation across states in indicators of schooling. For example, in rural Meghalaya, only 77 percent of primary schools had a pucca or partly pucca building.

Table 1
Indicators of schooling in various states of India

	% Pucca/Partly Pucca				**Pupil to teacher ratio**				**Schools**
	Primary	Upper primary	Secon-dary	Higher secon-dary	Primary	Upper primary	Secon-dary	Higher secon-dary	Available
A.P.	85.4	92.3	96.1	95.4	33	31	31	28	4.886
Assam	80.7	75.5	83.9	95.6	31	16	18	20	5.521
Bihar	89.3	92.5	94.8	95.0	85	76	49	23	2.024
Chhattisgarh	92.6	92.1	93.7	97.6	43	39	30	32	6.018
Goa	98.8	100	99.5	100	17	13	23	21	7.643
Gujarat*	90.2	98.8	95.9	99.1	28	38	34	37	3.946
Haryana	98.7	99.5	99.5	99.3	42	26	28	30	2.964
H.P	89.5	78.1	92.3	95.6	22	15	25	24	9.692
J&K	80.0	91.2	93.8	98.6	20	20	20	23	5.562
Jharkhand	92.3	94.7	98.1	100	59	60	43	30	3.018
Karnataka	96.2	99.1	97.0	99.8	27	38	26	33	4.787
Kerala	99.2	99.4	98.8	99.6	28	28	27	29	1.889
M.P	91.2	87.7	91.4	96.0	39	31	27	28	5.179
Maharashtra	97.8	98.7	91.8	98.0	30	35	33	39	4.162
Meghalaya	77.0	82.9	89.3	97.3	21	16	16	23	10.495
Orissa	95.1	91.7	95.1	100	43	40	23	19	5.838
Punjab	99.5	93.4	99.1	99.9	39	17	23	25	3.840
Rajasthan	97.7	97.3	99.9	100	42	34	28	28	3.773
Tamil Nadu	96.4	98.8	95.5	98.2	35	42	37	37	4.272
U.P	97.7	96.7	99.0	99.5	61	37	44	55	2.846
Uttarakhand	97.2	93.9	97.4	99.9	29	19	23	27	8.381
West Bengal	91.7	89.2	98.3	99.9	55	52	61	58	2.824

Pucca and Partly Pucca is calculated based upon data in Tables 22-25 in AISES (2008a).
For the definition of pucca, see footnote 7.

Pupil to Teacher Ratio (PTR) for primary, upper primary and secondary levels is taken from AISES (2008b), Table 59 and for higher secondary level is taken from AISES (2008c), Table 56. PTR = Number of Enrolled Students/Number of Teachers.

Schools available=1000*Total Number of Schools/Estimated number of children aged 16-18 as on 30 Sep 2002. The number of schools is taken from AISES (2008a), Tables 22-25 and the number of children from AISES (2008d), Table 3. * States in bold are in the ones in the ITUS sample.
Source: The Indian Time Use Survey, own calculations.

On the contrary, in rural Punjab, 99.5 percent of primary schools were thus constructed. All (i.e. 100 percent) upper primary schools in rural Goa had a good (i.e. pucca or partly pucca[6]) building, whereas the corresponding figure for Assam was only 75.5 percent.

6 A school is “pucca” if its walls are made of the following material: burnt bricks or stone or cement or concrete or timber; and its roof is made of tiles or GI (or metal or asbestos) sheets or concrete or bricks or stone or timber. A school is “partly pucca” if its walls are made of the same material as those used in the walls of a pucca school, but the roof is made of different material (e.g. grass, bamboo, thatch). The other kinds of

Similar variation existed at the secondary and higher secondary levels. The differences were more pronounced for Pupil-to-Teacher Ratios (PTRs). For rural primary and upper primary schools, the PTRs in Bihar were 85 and 76, respectively. The corresponding figures for Goa were only 17 and 13. The variation was comparable for secondary and higher secondary levels. Considerable variation also exists in the availability of schools.

There is considerable variation across the states in the ITUS sample (marked in bold in Table 1) which provides identifying variation for the analysis discussed below. As one would expect, states that are considered relatively underdeveloped are also the ones that are characterized by poor quality and availability of schools.

3 The probability of school attendance

Since the primary way in which children acquire human capital is by school attendance, we want to understand the factors influencing the likelihood that they will (or will not) attend school – which can be categorized as affecting either the demand for schooling or the supply of schooling.

Exploring the demand side first, individual and family characteristics influence the perceived net future returns (monetary and non-monetary) that families expect from schooling, which differ due to different families having different "tastes" for schooling, or differing opportunity costs of schooling or differing ability to finance schooling. Both in developing countries and in affluent OECD nations, the occupational and educational background of parents has long been recognized as the crucial determinant of children's educational attainment and the intergenerational transmission of socio-economic status.[7] Additionally, in the Indian context, caste is an important factor. Scheduled Caste or Tribe status could result in exclusion or discrimination in schooling facilities, or in the labour market.

On the supply side of schooling, the availability and quality of schools affects the expected net returns from schooling. As Hanushek et al. (2006) conclude: "a student is much less likely to remain in school if attending a low quality school rather than a high quality school." For most families, the availability and quality of schools in their local area is an exogenous constraint

schools are: kuchcha (walls and roof made of other material, e.g. unburnt bricks, bamboo, mud, grass); tent; open space (i.e. no building). See AISES (2007d, pp. 224-225).

7 See, for example, Dreze and Kingdon (2001), Jantti et al. (2006), Corak (2004, 2006), Blanden et al. (2007), and Wilson et al. (2007).

determining the family's schooling options.[8] In this paper, we therefore use state level AISES data on the availability and quality of schools, as explanatory variables.[9]

Within affluent OECD countries, all of which have well-developed systems of public education which provide universally available access to schooling of reasonably high quality, one could perhaps neglect the supply side – but India's context is different (as we saw in section 2.1). Although there is much discussion of inequalities of educational opportunity in the school system within, for example, the USA, the disparities among US states in availability, physical facilities and teacher student ratios are far smaller than among Indian states.

We use two indicators of quality, viz. the percentage of schools with good physical construction – pucca or partly pucca building – and the Pupil-Teacher Ratio, (which is more of a measure of teacher availability). Although teacher absenteeism, or performance on standardized test scores etc., would perhaps be better measures of actual school quality, that data is not available for us (or, for that matter, to parents) to use – and is arguably of less relevance to the decision-making of Indian parents than the characteristics of the school which they can actually directly observe themselves.

As mentioned earlier, this paper addresses the relative importance, in the context of rural India, of individual and household level characteristics which influence the demand for education, compared to the quality and availability of educational supply. Equation 1 summarizes the discussion.

$$(1) \qquad \Pr\left(S_i > 0\right) = f\left(X_i, F_i, Q_i\right).$$

S_i is the time spent by child i in school (including commuting time and homework). The probability that the child attends school ($S_i>0$) is determined by: X_i - a vector of characteristics of child i (e.g. age, gender); F_i - a vector of characteristics of the family that the child i belongs to (e.g. caste, education level of the household head); and Q_i - a vector of characteristics describing the availability and quality of schools in the state that the child i belongs to. We use a probit regression to estimate equation (1), considering separately, rural boys and girls, aged 6 to 10, 11 to 14 and 15 to 18.[10] We estimate these regressions separately because the assumption that the same model fits all these different age and gender groups may be unsustainable.

AISES data is used to construct for each state, variables indicative of the availability (number of schools per-capita[11]) and quality of the school system – the percentage of schools with good

8 Writing in the context of the variation in supply of local public good in the suburbs of US cities, Tiebout (1956) argued that individuals could move between jurisdictions to satisfy their preferences for local public goods supply. If this model were applicable to the Indian context, local school system characteristics would be endogenous to local household preferences: but the nature of schooling in India and the more limited migration of Indian households for education (NSSO 2000) makes this a poor assumption, in this context.

9 In doing so, we recognise that within-state variability in local school quality can create attenuation bias, biasing downward the size and statistical significance of any estimated coefficient.

10 Given that there is controversy and debate regarding whether weights should be used in regressions (see Deaton 1997, Section 2.1), we present results with unweighted regressions.

11 We compute the per-capita measures by dividing the total number of schools (Primary to Higher Secondary) by the number of "potential" students, i.e. children in the age group 6-18 (Table 2, AISES (2007a)).

infrastructure (pucca or partly pucca buildings) and the Pupil to Teacher Ratio (PTR). In each state, household micro-data from the ITUS is matched, using the geo-codes on each file, to the corresponding state-level indicators of availability and quality from the AISES.

Table 2 presents descriptive statistics for the sample[12]. In addition to the above independent variables, two other variables (number of females aged 15 or above in the household, and time spent by the household in fetching water) are used in the regression on human capital accumulation time (discussed below). We also present the descriptive statistics for these variables, for the total human capital allocation time, and its three components (school time, home work time and travel time).

Because we run separate regressions for boys and girls and for each age group, we report separately the descriptive statistics for each sample – but we would not generally expect to observe big differences between columns[13]. In our data, it is notable that the majority (roughly 57%) of children live in households which have a self-employed head, with less than a primary education and have no literate adult female in the household. Just under 40% of the households are landless and about a third are Scheduled Caste or Scheduled Tribe (SC or ST). Female headed households are not an insignificant fraction – even in rural India, about 8% of children live in such households. Although we present here the time spent on water collection as an average over all households, arguably that understates the time burden on those households who have to collect water (see Motiram and Osberg 2010a for more discussion).

As we can observe from table 2, sample sizes for girls are lower than the same for boys due to an adverse sex-ratio prevailing in India. As mentioned above, attendance rates for boys are higher than the same for girls for all age cohorts. Similarly, the total time spent on human capital accumulation (and its three components) for boys is higher than the same for girls – this is largely a reflection of differences in attendance rates.[14] Table 2 shows time spent on education averaged over all children of the same age and gender, including those who do not attend school. The differences between boys and girls, and the drop-off in school attendance with age explain the declining average time investment in human capital as children age (for a fuller discussion see Motiram and Osberg 2010b). None the less, Table 2 also reveals the importance of homework as a proportion of total human capital investment time.

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12 In the interests of space, given that we have six regressions, we have presented only the mean and standard deviation. The maximum and minimum values are available upon request. Also note that some dependent variables are dummies and therefore have a minimum value of zero and maximum value of 1.

13 Households containing older children have somewhat higher average per capita monthly expenditures, no doubt due to the earnings of teenagers, but the difference is not statistically significant.

14 Since only those children attending school would spend time accumulating human capital.

Table 2
Descriptive statistics, individual and household variables

	6-10		**11-14**		**15-18**	
	Boys	Girls	Boys	Girls	Boys	Girls
Age in years	8.426	8.411	12.517	12.561	16.481	16.577
	(1.278)	(1.313)	(1.046)	(1.051)	(1.199)	(1.185)
Monthly per-capita	408.086	388.410	430.680	422.432	462.043	449.474
Expenditure (in Rs.)	200.186	181.911	225.816	201.044	233.659	237.619
			Fraction			
Currently married[a]					0.019	0.141
					(0.136)	(0.348)
Self employed[a]	0.563	0.559	0.563	0.568	0.579	0.585
	(0.496)	(0.497)	(0.496)	(0.496)	(0.494)	(0.493)
Other employed[a]	0.099	0.098	0.104	0.109	0.102	0.098
	(0.298)	(0.297)	(0.305)	(0.312)	(0.303)	(0.298)
Landless[a]	0.395	0.392	0.383	0.379	0.374	0.370
	(0.489)	(0.488)	(0.486)	(0.485)	(0.484)	(0.483)
SC or ST[a]	0.375	0.408	0.331	0.322	0.329	0.321
	(0.484)	(0.492)	(0.471)	(0.467)	(0.470)	(0.467)
Female headed[a]	0.071	0.072	0.071	0.086	0.090	0.106
	(.256)	(0.259)	(0.257)	(0.281)	(0.287)	(0.307)
No literate female	0.588	0.580	0.520	0.480		
Adult (older than 15)[a]	(0.492)	(0.494)	(0.500)	(0.500)		
No literate female					0.583	0.556
Adult (older than 18)[a]					(0.493)	(0.497)
			Education of household head			
Below primary[b]	0.556	0.581	0.597	0.656	0.583	0.583
	(0.497)	(0.493)	(0.491)	(0.475)	(0.493)	(0.493)
Primary[b]	.401	0.420	0.451	0.476	0.434	0.437
	(0.490)	(0.494)	(0.498)	(0.500)	(0.496)	(0.496)
Middle[b]	0.256	0.256	0.292	0.300	0.268	0.264
	(0.437)	(0.436)	(0.455)	(0.458)	(0.443)	(0.441)
Secondary[b]	0.129	0.131	0.138	0.154	0.138	0.137
	(0.335)	(0.337)	(0.345)	(0.361)	(0.345)	(0.344)
H. Secondary[b]	0.055	0.052	0.060	0.060	0.056	0.059
	(0.228)	(0.223)	(0.237)	(0.237)	(0.230)	(0.236)
Grad or above[b]	0.020	0.019	0.022	0.026	0.026	0.020
	(0.141)	(0.136)	(0.148)	(0.160)	(0.158)	(0.140)

Table 2 Cont.
Descriptive statistics, individual and household variables

	6-10		11-14		15-18	
	Boys	Girls	Boys	Girls	Boys	Girls
Winter (Season dummy[c])	0.192	0.190	0.174	0.190	0.179	0.176
	(0.394)	(0.392)	(0.379)	(0.392)	(0.384)	(0.381)
Summer (Season dummy[c])	0.265	0.248	0.244	0.242	0.257	0.265
	(0.442)	(0.432)	(0.430)	(0.428)	(0.437)	(0.442)
Post-monsoon	0.267	0.252	0.257	0.254	0.249	0.247
	(0.442)	(0.434)	(0.437)	(0.436)	(0.432)	(0.431)
Attending school[a]	0.700	0.658	0.661	0.556	0.327	0.208
	(0.458)	(0.474)	(0.474)	(0.497)	(0.469)	(0.406)
Number of females	1.325	1.341	1.432	1.457	1.468	2.214
Above 15 years	(0.701)	(0.712)	(0.785)	(0.797)	(0.771)	(0.936)
Time spent by HH on	8.908	9.240	11.618	13.623	13.102	15.279
Water collection[d]	(26.412)	(28.276)	(31.276)	(36.236)	(32.836)	(37.729)
In-class time (S_i)[d]	217.524	204.634	212.716	179.446	105.198	68.115
	(156.546)	(159.211)	(164.610)	(170.724)	(159.090)	(140.080)
Homework time (H_i)[d]	79.066	73.627	95.144	80.194	61.782	37.958
	(94.322)	(90.313)	(105.108)	(103.304)	(108.472)	(89.896)
Travel time (T_i)[d]	27.326	25.292	31.686	25.055	20.784	12.025
	(31.024)	(35.416)	(37.981)	(35.181)	(39.602)	(29.144)
Human capital time [d]	310.282	291.910	325.511	272.070	172.996	107.610
	(222.182)	(227.984)	(249.023)	(256.955)	(256.695)	(216.635)
Observations	2409	2002	1839	1678	2062	1658

Note. The values reported are means. The values in parentheses () are standard deviations. Both are for the sample (i.e. not using the sampling weights).

(a). Dummy variables, 1=Yes and 0=No. For marital status, there are four possibilities: (i) never married, (ii) currently married, (iii) widowed, and (iv) divorced or separated. Only a few (7) among those aged 15-18 fall into this category, and these are all girls.

(b). These dummies refer to the education levels of the Household Head.

(c). =1 if a child is surveyed in a particular season, and 0 if not. For a description of these seasons, see p. 10.

(d). All times in minutes per normal day.

Source: The Indian Time Use Survey, own calculations.

Table 3 presents the descriptive statistics for the school quality variables. Note that there are six states in the sample and these statistics are computed based upon six observations, one for each state, for each variable. As we noted above, there is considerable variation across states in terms of their quality indicators.

Table 4 presents the estimates from the probit regression. A consistent finding in Table 4, with only a few exceptions, is the statistically significant (at 1%) positive correlation between school attendance and our indicator of high quality school construction. Similarly, with a few exceptions, as expected, the coefficient on PTR is large, negative and statistically significant (at 1% or 5%). Except for the highest age group (15-18) and boys aged 11-14, the coefficient for the availability of schools is consistently positive and statistically significant (at 1%).

In Table 4, a [0,1] dummy variable identifies households in which there is no literate adult female (e.g. mother or elder sister). For both boys and girls, for all age groups, this variable comes through very strongly – statistically significant (at 1% or 5%) and negatively correlated with school attendance.

Table 3
Descriptive statistics, School quality variables

School quality variables	
% Pucca or partly pucca schools (primary)	0.915
	(0.078)
% Pucca or partly pucca schools (upper primary)	0.932
	(0.069)
% Pucca or partly pucca schools (secondary and h. secondary)[a]	0.952
	(0.032)
PTR (primary)	34.667
	(8.641)
PTR (upper primary)	32.167
	(9.928)
PTR (secondary and higher secondary)[b]	28.189
	(7.456)
Number of schools per-capita	5.449
	(2.665)

Note: (a). See notes to table 1.

(b). The combined (Secondary and H. Secondary) value is obtained in the following manner: Number of Pucca or Partly Pucca Secondary and Higher Secondary Schools/Total Number of Secondary and Higher Secondary Schools.

The combined PTR (Secondary and H. Secondary) is obtained in the following manner: (PTR (Secondary)*Number of Secondary Teachers+PTR (H. Secondary)*Number of H. Secondary Teachers)/The number of Secondary and Higher Secondary teachers. The number of Secondary and Higher Secondary teachers are taken from AISES (2008b) and AISES (2008c), respectively.

Source: The Indian Time Use Survey, own calculations.

The educational background of the head of each household is measured by a series of dummy variables indicating the marginal influence of schooling attainment, relative to lower levels of school attainment. The base case is a household head with no formal education, so a [0,1] dummy variable indicates whether the head has some primary school, another [0,1] dummy variable indicates whether the head has finished primary school, and another [0,1] dummy variable indicates whether the head has finished middle school etc. Anyone who has finished primary school will necessarily be coded [1] for both “some primary” and “finished primary”, while a middle school graduate will be coded [1] for each of “some primary”, “finished primary” and “finished middle school” – so the cumulative influence of education is the sum of coefficients at earlier levels of education.

Table 4
Probit model for the determinants of attendance
(dependent variable: 1 if child is attending school and 0 if not)

	6-10		**11-14**		**15-18**	
	Boys	Girls	Boys	Girls	Boys	Girls
Age in years	-0.063***	-0.059**	-0.119***	-0.180***	-0.298***	-0.395***
	(0.023)	(0.024)	(0.031)	(0.032)	(0.027)	(0.038)
Currently married					-0.630*	-0.391*
					(0.357)	(0.210)
Self employed	-0.074	-0.129*	-0.136	-0.029	0.107	-0.032
	(0.073)	(0.078)	(0.083)	(0.086)	(0.083)	(0.110)
Other employed	0.217*	0.142	0.512***	0.182	0.207*	0.016
	(0.121)	(0.130)	(0.139)	(0.127)	(0.118)	(0.149)
Landless	-0.081	-0.054	-0.132*	-0.050	0.062	0.051
	(0.069)	(0.074)	(0.079)	(0.082)	(0.077)	(0.099)
Monthly per-capita	-0.009	0.042**	-0.023	0.045**	0.052***	0.077***
Expenditure (100s of Rs.)	(0.017)	(0.021)	(0.016)	(0.019)	(0.014)	(0.017)
SC or ST	-0.193***	-0.195***	-0.045	-0.112	-0.028	-0.031
	(0.064)	(0.066)	(0.073)	(0.076)	(0.072)	(0.098)
Female headed	-0.127	-0.036	0.020	-0.070	-0.013	-0.004
	(0.115)	(0.127)	(0.130)	(0.121)	(0.112)	(0.132)
No literate female	-0.172**	-0.493***	-0.292***	-0.497***		
Adult (older than 15)	(0.073)	(0.075)	(0.075)	(0.076)		
No literate female					-0.288***	-0.517***
Adult (older than 18)					(0.074)	(0.093)
Below primary	0.343***	0.229**	0.306***	0.255***	0.147	0.025
	(0.089)	(0.094)	(0.099)	(0.098)	(0.098)	(0.133)
Primary	-0.046	0.057	-0.047	0.221**	0.148	0.215
	(0.110)	(0.110)	(0.114)	(0.109)	(0.107)	(0.141)
Middle	-0.072	-0.005	0.289**	0.060	0.203*	0.386***
	(0.116)	(0.123)	(0.120)	(0.118)	(0.110)	(0.135)
Secondary	0.212	0.201	0.104	0.109	-0.007	-0.126
	(0.147)	(0.157)	(0.159)	(0.145)	(0.130)	(0.159)
H. secondary	-0.256	0.001	-0.116	0.077	0.196	0.256
	(0.205)	(0.231)	(0.229)	(0.229)	(0.198)	(0.211)
Grad or above	0.155	-0.136	0.504	0.181	0.056	-0.088
	(0.278)	(0.324)	(0.347)	(0.329)	(0.253)	(0.290)
% Pucca or partly	12.342***	9.198***				
Pucca schools (primary)	(1.689)	(1.783)				
% Pucca or partly			3.287***	3.866***		
Pucca schools (upper pr.)			(1.097)	(1.120)		

Table 4 Cont.
Probit model for the determinants of attendance,
(dependent variable: 1 if child is attending school and 0 if not)

	6-10		11-14		15-18	
	Boys	Girls	Boys	Girls	Boys	Girls
% Pucca or partly					5.838 **	0.107
Pucca schools (secondary and h. secondary)					-2.540	-3.712
PTR (Primary)	-0.050 ***	-0.049 ***				
	(0.009)	(0.010)				
PTR (Upper Primary)			-0.007	-0.015 **		
			(0.006)	(0.007)		
PTR (Secondary and Higher Secondary)					-0.030 ***	-0.014
					(0.008)	(0.010)
No. of Schools	0.147 ***	0.150 ***	0.033	0.151 ***	0.029	0.055
Per-capita	(0.039)	(0.041)	(0.042)	(0.041)	(0.048)	(0.065)
Winter (Saison dummy)	0.611 ***	0.245 ***	0.386 ***	0.209 **	0.040	0.332 ***
	(0.090)	(0.093)	(0.099)	(0.097)	(0.090)	(0.115)
Summer (Saison dummy)	-0.565 ***	-0.750 ***	-0.500 ***	-0.626 ***	-0.499 ***	-0.329 ***
	(0.074)	(0.082)	(0.083)	(0.089)	(0.086)	(0.111)
Post-Monsoon	0.485 ***	0.106	0.302 ***	0.065	0.109	0.136
	(0.081)	(0.085)	(0.086)	(0.089)	(0.080)	(0.106)
Constant	-9.185 ***	-6.284 ***	-0.963	-1.516	-0.697	5.336
	(1.495)	(1.589)	(1.159)	(1.176)	(2.691)	(3.908)
Observations	2409	2002	1839	1678	2062	1658

*** 1%, ** 5%, * 10%, The values in parentheses () are standard errors.
Note. For a description of these variables, see notes to tables 2 and 3.
Source: The Indian Time Use Survey, own calculations.

It is evident that for both boys and girls aged 6 to 10, a crucial issue in attendance at primary school is whether or not one's parents have *any* education.[15] Compared to the base case of no formal education, the dummy variable for "some primary" is a strongly significant (statistically significant at 1% or 5%) determinant of school attendance for both boys and girls.

The statistical insignificance of higher levels of school attainment indicates that among parents with higher schooling levels, there is no particular difference in their desire for primary school attendance by their children. However, for children in higher age groups, higher educational levels play a role, e.g. for girls aged 11-14, the coefficient on primary education is statistically

15 About 87% of children aged 6 to 18 are unmarried children of the household head. So, we use term "parent" for ease of exposition.

significant (at 5%) and positively associated with attendance. Broadly speaking, we can interpret these findings as indicative of an escalating intergenerational norm within families for more education.

Current household income is approximated in the ITUS by aggregate monthly expenditure per capita. The respondents to the ITUS were asked a single summary question about total average monthly expenditures by the household rather than the series of questions on categories of consumption which a household expenditure survey would use, to add up total consumption. We are therefore cautious about possible measurement error in this variable[16] – particularly since it is unlikely to include self-production of food and fuel. Nevertheless, income is uncorrelated with the school attendance of boys aged 6 to 10 and 10 to 14 (columns 1 and 3). However, the positive and statistically significant coefficients in columns 2 and 4 (at 5%) indicate that family income matters for similarly aged girls – i.e. there is some evidence of interaction between economic disadvantage and gender bias in early schooling. More generally – over and above the direct influence of parental education – the statistically significant (at 1%) positive correlation of household income and school attendance for both boys and girls ages 15 to 18 is an important indicator of inequality of opportunity.

Columns 1 and 2 indicate that the social disadvantage of membership in a Scheduled Caste or Tribe[17] is directly correlated with lower early school attendance, in addition to the influence of household income or parental education, but columns 3 to 6 show no statistically significant correlation with later attendance. In the highest age group (15 to 18), since it is possible that a child could be married (although the legal age for marriage is 18 for girls, and 21 for boys), we controlled for marital status. As expected, a child is less likely to attend if he/she is currently married.[18] We controlled for the occupational status of the household by taking a labourer household as the base with the other categories being self-employed (in agriculture or non-agriculture) and others. As can be seen from table 2, the results are not consistent across the age and gender groups, although there is some evidence that attendance varies across occupational categories. Although we include a dummy variable for female household head status and another for landlessness, neither is statistically significant, once we have controlled for income and education.

The ITUS was conducted in different months of the year and the date of the normal day was recorded for each respondent. Since Indian rural economy and society (like in other developing countries) is dominated by agriculture, we used seasonal dummies. We considered the following seasons, based upon the climate profile for India (IMD 2011): winter (January, February,

16 Our caution is also partly due to the relatively small reported differentials in monthly expenditure for households with large differentials in land owned. The correlation between monthly per-capita expenditure and land ownership is also very low (0.16).

17 There is extensive literature on the Indian caste system and its implications for development. See Chatterjee (1993), Gupta (1993) and Dreze and Sen (2002).

18 ITUS divides individuals into four categories based upon marital status – (i) never married, (ii) currently married, (iii) widowed and (iv) divorced/separated. As is expected (since we are dealing with children), there are very few (7) individuals in the last two categories, and that too only among girls.

December (for Haryana and Gujarat)), summer (March, April, May), South West monsoon (June to September) and post-monsoon/North East monsoon (October, November, December (for states other than Haryana and Gujarat)). The base category we used is the South West monsoon. We find some evidence that during the monsoon (when a considerable amount of agricultural work is required), children are not in school – probably pulled out of school to work. The coefficient on the winter and post-monsoon dummies are positive and statistically significant for some age and gender groups. The coefficient on the dummy for summer is negative since schools are generally closed during the summer.

4 Time invested in education

Time use data enables a much better picture of human capital investment, since the total time invested in education by each child i (HK_i) is the sum of the time he/she spends in class (S_i) plus the time he/she spends doing homework (H_i) plus travel time (T_i), to and from school – as equation (2) summarizes.

(2) $$HK_i = S_i + H_i + T_i \,.$$

Generally speaking, it is not possible to attend school for ½ or ¾ hours each day, which implies that the normal school day is a "lump" of time. On any given day, some of the children who would normally be in school will be absent, due to competing work responsibilities, or because they want to skip school. We only observe S_i for those children who actually attend school on the day surveyed by ITUS, so the estimation of expected HK_i is a classic "sample selection bias" problem in the sense of Heckman (1979). Hence, we include as an explanatory variable, the Inverse Mills Ratio (IMR) (denoted as λ_i) derived from the probit estimation of equation (1) above. We also include W_i – time allocated to other activities within the household, which may influence the time allocated to human capital accumulation. A general form of the equation can then be summarized as:

(3) $$E\left(HK_i\right) = g\left(X_i, F_i, Q_i, W_i, \lambda_i\right).$$

i is the index for the child. X_i, F_i, Q_i as defined earlier (in (1)), are the vectors of child characteristics, family characteristics, and availability and quality of schooling, respectively. In other work[19], we have found that 16% of households in rural India have to spend time collecting water (a highly gendered task) for daily use. For the development process, an important implication of carrying water is its possible impact on human capital acquisition – specifically, on the time that children will spend in school, travelling or doing homework. Rural women who spend an average of 47 minutes per normal day carrying water do not have that time available to spend attending to their children – unless perhaps they can delegate the task of fetching water to their teenage daughters, which may be part of the reason their daughters withdraw from school.

[19] Motiram and Osberg (2010a) presented data on the gendered burden of water carrying, and explored the determinants of piped water availability.

Even if children are not asked to carry water themselves, the fact that someone (usually the mother) has to spend time on this task means that children may be asked to perform other household chores – which implies that total household time spent in water collection may affect school attendance and human capital investment[20]. Given that Table 4 shows the importance of adult female education for the school attendance of their children, this impact of water collection time on female investment in education can be expected to have implications over many future generations. We also include the number of women in the household aged 15 or higher since the task of collecting water can be spread over several members.

From the perspective of costs to the household, all the three component activities (i.e. school, home work and travel) are part of the cost of human capital investment, since they all take away from competing uses of time. However, viewed from the perspective of returns to investment, one could consider school and home work time as "productive" and travel as "unproductive." It is not obvious, a priori, if the time spent on homework complements or substitutes for school time – homework could either increase or decrease with quality of the school that the child attends.

In table 5, we report estimates of equation (2) for boys and girls for three age groups (6-10, 11-14 and 15-18). We ran both Ordinary Least Squares (OLS) and "Heckit" estimates (i.e. OLS estimates with the Inverse Mills Ratio (IMR) added as an explanatory variable). As is standard, where the IMR is statistically significant (at 5%), we prefer, and therefore report the Heckit estimates. Where this is not the case (i.e. not statistically significant), we report the OLS estimates. There is evidence of sample selection only at the youngest age group, for both boys and girls.

Except for boys aged 11-14, in all age groups, and for both genders, the amount of time a household has to spend collecting water for daily use is negatively correlated with the amount of time spent on the education of children. Public policy on water delivery therefore affects both current and future well-being. The availability of tap water matters directly for the well-being of the women who would otherwise have to perform the daily drudgery of carrying water and indirectly for the future earnings and well-being of the children whose investment in education is lessened.

Public policy on the availability and quality of schooling also has a clear impact. For both boys and girls, the quality of school buildings and the availability of schools are strongly statistically significant and positively associated with the human capital investment time of children.

Another lesson from table 5 is the non-homogeneity of impacts by level of education. For example, whether a child comes from a Scheduled Caste or Scheduled Tribe family is not statistically significant for time spent on early education (ages 6 to 10), but is statistically significant and negatively associated with time spent in later years: 11 to 18 (for both boys and girls).

[20] Note that water-carrying time is measured at the household level, so it could all be done by adults - there is no necessary subtraction from the time available for school of any particular child.

Table 5
Determinants of human capital accumulation time of children
(dependent variable: Human capital accumulation time in mins/normal day)

	6-10		**11 -14**		**15-18**	
	Boys	Girls	Boys	Girls	Boys	Girls
Age (in years)	14.461 ***	13.419 ***	9.426 ***	9.903 ***	3.114	-5.868
	(2.275)	(2.490)	(2.778)	(3.212)	(3.867)	(6.531)
Currently married					21.171	-17.418
					(78.119)	(48.804)
Self employed	6.876	27.279 ***	-11.478	1.770	-21.963 *	8.858
	(6.239)	(7.397)	(7.862)	(9.079)	(11.785)	(19.337)
Other employed	-3.151	15.613	12.030	31.215 ***	-2.048	2.429
	(9.539)	(10.470)	(10.039)	(11.834)	(15.157)	(22.946)
Landless	6.896	8.419	-17.812 **	-6.675	-18.083 *	8.397
	(5.808)	(6.368)	(7.264)	(8.284)	(10.428)	(16.335)
Monthly per-capita	-2.538 *	-6.645 ***	-4.997 ***	-9.035 ***	0.185	-3.949
Expenditure (100s of Rs.)	(1.311)	(1.821)	(1.409)	(1.774)	(1.777)	(2.667)
SC or ST	-6.143	1.425	-17.219 **	-30.730 ***	-35.790 ***	-37.299 **
	(6.718)	(7.915)	(6.801)	(8.194)	(10.380)	(16.478)
Female headed	12.456	13.440	9.317	-27.066 **	-18.688	-9.735
	(10.053)	(10.626)	(11.723)	(12.855)	(15.912)	(21.033)
No literate female	1.352	30.849 **	-5.022	-8.788		
Adult (older than 15)	(6.817)	(13.640)	(7.148)	(8.644)		
No literate female					8.251	-23.298
Adult (older than 18)					(10.567)	(16.650)
Below primary	-9.621	-12.565	-4.223	3.519	-0.088	16.427
	(10.137)	(10.680)	(9.450)	(11.263)	(14.566)	(23.631)
Primary	6.045	-24.108 ***	0.630	-13.230	-38.828 **	-27.591
	(8.293)	(9.085)	(10.450)	(11.280)	(15.047)	(23.283)
Middle	0.497	4.807	14.115	19.773 *	28.686 **	16.251
	(8.714)	(9.460)	(9.947)	(11.084)	(14.310)	(20.235)
Secondary	-15.298	-9.333	-9.333	-8.733	8.692	-37.369 *
	(10.653)	(11.812)	(11.455)	(12.691)	(16.194)	(21.567)
H. secondary	31.055 **	27.436 *	15.407	18.890	2.299	40.949
	(15.262)	(15.987)	(16.497)	(18.663)	(22.380)	(27.166)
Grad or above	-28.560	-9.919	15.982	-5.074	-36.120	-5.338
	(19.953)	(22.059)	(21.492)	(23.641)	(27.199)	(35.821)
% Pucca or partly	1272.239 ***	1291.079 ***				
Pucca schools (Primary)	(272.504)	(262.559)				
% Pucca or partly			558.231 ***	463.390 ***		

Table 5 Cont.
Determinants of human capital accumulation time of children
(dependent variable: Human capital accumulation time in mins/normal day)

	6-10		11-14		15-18	
	Boys	Girls	Boys	Girls	Boys	Girls
Pucca schools (Upper primary)			(112.404)	(122.217)		
% Pucca or partly					2613.852 ***	2258.224 ***
Pucca schools (Secondary and h. secondary)					(359.884)	(601.186)
PTR (Primary)	-2.813 **	-2.395 *				
	(1.201)	(1.440)				
PTR (Upper primary)			2.792 ***	3.199 ***		
			(0.609)	(0.694)		
PTR (Secondary)					2.168 **	2.042
PTR (Higher secondary)					(1.093)	(1.649)
No. of schools	16.137 ***	17.507 ***	21.029 ***	15.431 ***	38.717 ***	29.508 ***
Per-capita	(4.144)	(4.994)	(4.230)	(4.035)	(6.575)	(10.301)
Number of females	-1.788	7.097*	4.092	3.147	12.293 **	13.074 *
Above 15 years	(3.354)	(3.720)	(3.955)	(4.356)	(5.288)	(7.244)
Time spent by HH on	-0.349 ***	-0.366 ***	0.005	-0.217 **	-0.661 ***	-0.422 **
Water collection	(0.090)	(0.102)	(0.106)	(0.102)	(0.136)	(0.175)
Season dummy Winter	-26.608 *	-10.240	15.817 *	5.694	16.988	26.106
	(13.777)	(9.469)	(8.222)	(9.516)	(12.230)	(17.572)
Season dummy Summer	-24.915	26.269	-36.407 ***	-25.091 **	-12.043	16.318
	(15.630)	(22.515)	(8.573)	(10.374)	(12.975)	(19.576)
Post-Monsoon	-8.599	3.469	1.548	9.215	20.361 *	40.619 **
	(11.111)	(7.196)	(7.439)	(8.817)	(10.818)	(16.747)
Inverse Mills Ratio	-105.685 **	-178.381 ***				
	(46.699)	(53.772)				
Constant	-766.056 ***	-785.004 ***	-315.308 ***	-210.905 *	-2250.739 ***	-1764.268 ***
	(240.219)	(229.418)	(116.266)	(127.484)	(382.770)	(642.485)
Observations	1686	1318	1215	933	675	345
R-squared	0.223	0.231	0.144	0.163	0.145	0.138

*** 1%, ** 5%, * 10%, The values in parentheses () are standard errors.

Note. For a description of these variables, see notes to tables 2 and 3.

Source: The Indian Time Use Survey, own calculations.

In the labour supply literature, a distinction is often drawn between the “extensive margin” of labour supply (as when people who were not previously working get a job) and the “intensive margin” (as when people who are already working decide to supply more or fewer work hours). The same terminology is useful here. Reading Tables 4 and 5 together, Table 4 shows that the presence of literate females in the household is important for the “extensive margin” (i.e. for school attendance), but table 5 indicates that, conditional on school attendance, this variable is not important at the “intensive margin” (i.e. in determining the amount of time spent *by students* on their schooling).[21] Similarly, the education of the head of household seems to matter more at the extensive margin of attendance than at the intensive margin of hours studied.

Income (more exactly, monthly per-capita expenditure) does not have a robust association. It has a statistically significant *negative* association for 6 to 10 year old girls and 11 to 14 year old boys and girls. The “perverse” sign could be due to measurement error of this variable (which we discussed above) or due to children from richer households attending better schools – note that quality could either lead to higher or lower time on home work.

5 Quantitative implications

In rural India in 1999, over thirty percent of boys aged 11 to 14, and over forty percent of girls, did not attend school. Tables 4 and 5 report the correlates, across individual households, of school attendance and human capital investment time – but what do Tables 4 and 5 imply about which factors might matter more? How much was due to the barriers of caste? How much did the poor education of parents, which might produce ignorance of the benefits of education, actually matter? Is low family income, and a consequent need for immediate earnings by children, the key factor? Or is the quantitatively important explanation to be found in the low quality of the education which is available or the simple lack of schools?

To address these questions, we explore the quantitative implications of the econometric estimates of the determinants of school attendance (reported in Table 4) and the investment time estimates (reported in Table 5). We perform five “thought experiments”, assuming that the influence of all the other covariates reported in Tables 4 and 5 remains constant:

(A) Remove the influence of Scheduled Caste or Tribe (SC/ST) membership.

(B) Assume that all families have incomes of Rs. 400[22] or more (i.e. all families with less income than the median for rural households are brought up to that level).

(C) Assume that all heads of household have at least a high school (i.e. upto secondary level) education.

(D) Assume that all families have at least one literate female adult.

[21] Which also implies that it would have been inappropriate to use a single equation Tobit specification for estimation of the determinants of HK_i.

[22] This is the median household monthly per-capita income for rural households.

(E) Increase the quality and availability of local schooling to the sample median, in those states that fall below the median.

We report the results of these calculations in Table 6. Although simulation E (increasing quality and availability of all schools to the sample median) is intended as an example of feasible policy intervention, simulations A to C are not intended to be "realistic". Rather, the intention is to illustrate, for comparison purposes, the impacts associated with "large" changes (e.g. the end of caste status in India – Simulation A). We do not pretend that such changes are feasible policy choices.

The "No Change" simulation is performed in the following manner. We use estimates from Table 4 and a random error term that we generate[23] to predict for each child (*i*), his/her probability of attendance, p_i. We then compare this probability p_i with a random variable (X) that we generate from the uniform distribution with support [0,1]. We set the child *i* as attending if $p_i > X$ and as not attending, otherwise. We can now calculate the simulated attendance rate for the entire sample using this information (i.e. attending or not attending) for each child. We perform 1000 simulations and report the simple average attendance rate in Table 6. For human capital investment time, we do the following. For each child (*i*), if the child is not attending (from the above simulation on attendance), we set this time to be zero. Otherwise, we use the estimates from Table 5 and a random error term that we generate[24], to get the predicted human capital investment time (H_i). We then compute the median and median over all positive values. We perform 1000 simulations and compute a simple average of these medians and report it in Table 6.

For each of the thought experiments (A)-(E) above, we perform a simulation similar to the above. The only difference is that for each experiment, we change the attributes of certain children – e.g. in experiment (A), we take every child who belongs to Scheduled Caste (SC) or Scheduled Tribe (ST) and set him/her as non-SC or ST; in experiment (B), we take all children who have a household monthly per-capita expenditure less than the median (Rs. 400) and set their monthly per-capita expenditure as Rs. 400; in experiment (E), we raise to median quality and availability of schooling, the quality and availability of schooling for all children who are associated with less than the median. Note that in all the cases, those children who are already associated with the "superior" value of the attribute are untouched, e.g. those children who are associated with monthly household per-capita expenditure of Rs. 400 or more are left alone.

The differences (between each simulated outcome and No Change) can be interpreted as the simulated outcomes of these policy thought experiments. In presenting these results, we are aware that we are comparing a plausible policy scenario about changes to the supply of schooling (raising school quality and availability to the observed median) with several far less plausible scenarios (e.g. no rural household having income less than the 1999 median), which might

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23 Given that this is a probit model, this error term is drawn from the standard normal distribution.

24 This is drawn from a normal distribution with mean 0 and variance equal to the variance of the error term from the regression of the determinants of human capital investment time (equation (3)). As is well known, an unbiased predictor of this variance is the root mean square error from the regression – which we use.

affect the demand by households for education. We believe that attenuation bias due to measurement error will mean that we have probably *underestimated* the true association between school quality and schooling choices. Nevertheless, our basic conclusion is that the influence of the supply of poor school quality on the school attendance decisions of rural families in India is large relative to the influence of personal characteristics like scheduled caste membership or low household income.

Table 6
Results of simulation on quantitative implications

	6-10		11-14		15-18	
	Boys	Girls	Boys	Girls	Boys	Girls
			No change[a]			
Attendance	65.50 %	61.80 %	62.60 %	53.80 %	36.10 %	25.20 %
Attendance (SC/ST)	60.90 %	56.30 %	58.60 %	47.50 %	32.20 %	19.90 %
HK time (median)[b]	365.24	346.66	400.93	320.92	0	0
HK time>0 (median)	442.48	441.72	492.25	489.58	531.37	515.19
HK time (median, SC/ST)	331.85	294.98	362.56	39.83	0	0
HK time>0 (median, SC/ST)	432.31	429.62	477.26	469.02	508.14	485.36
			Simulation A[c]			
Attendance	67.30 %	63.90 %	63.10 %	54.90 %	36.50 %	25.30 %
Attendance (SC/ST)	65.60 %	61.40 %	59.80 %	50.40 %	33.10 %	20.30 %
HK time (median)	373.67	355.06	408.98	347.69	0	0
HK time>0 (median)	443.88	440.35	497.53	498.71	541.87	524.13
HK time (median, SC/ST)	360.06	329.36	388.26	164.7	0	0
HK time>0 (median, SC/ST)	437.13	427.75	494.45	499.99	543.62	521.75
			Simulation B[d]			
Attendance	65.30 %	62.60 %	62.30 %	54.60 %	36.90 %	25.90 %
HK time (median)	362.85	346.16	397.11	329.32	0	0
HK time>0 (median)	440.71	437	489.1	484.72	531.75	513.59
			Simulation C[e]			
Attendance	71.90 %	69.50 %	72.60 %	62.90 %	43.50 %	31.22 %
HK time (median)	371.24	351.33	437.46	397.31	0	0
HK time>0 (median)	426.65	416.27	490.74	489.34	537.77	485.82
			Simulation D[f]			
Attendance	68.10 %	69.50 %	66.70 %	60.50 %	40.50 %	31.00 %
HK time (median)	373.34	355.54	420.41	387.49	0	0
HK time>0 (median)	440.71	421.24	493.3	492.45	526	523.31

Table 6 Cont.
Results of simulation on quantitative implications

	6-10		11-14		15-18	
	Boys	Girls	Boys	Girls	Boys	Girls
			Simulation E[g]			
Attendance	73.60 %	69.20 %	66.00 %	59.70 %	46.60 %	28.60 %
Attendance (SC/ST)	69.40 %	64.50 %	62.40 %	53.60 %	43.60 %	22.80 %
HK time (median)	422.95	409.37	433.7	389.42	1.14	0
HK time>0 (median)	471.73	471.77	506.61	496.26	561.57	533.89
HK time (median, SC/ST)	399.36	381.04	405.87	290.57	0.54	0
HK time>0 (median, SC/ST)	461.04	462.69	494.23	478.52	543.07	509.3

Note:
a. The No Change and other simulations are explained in great detail on pp. 14-15.
b. All medians in minutes per normal day.
c. Removes the impact of SC/ST.
d. Takes children in households with less than median income to the median.
e. Sets the education level of the household head to at least high school.
f. Ensures that there is at least one literate female adult in the household.
g. For children in states lying below the median quality and availability of schooling, makes these equivalent to the median.
Source: The Indian Time Use Survey, own calculations.

Because most people are not members of Scheduled Castes or Scheduled Tribes, most people are therefore not themselves affected by the marginalization of SC/ST members, so there is not a large aggregate impact, for the population as a whole, when the stigma of membership in these groups is removed – e.g. for 6 to 10 year olds, we simulate an increase of 1.8 percentage points in the school attendance of boys, and 2.1 percentage points for girls. However, one should not think of the SC/ST issue just in terms of aggregate human capital formation and aggregate growth. If, for the same age group, one considers only members of scheduled castes and tribes, the change in attendance rates and median human capital investment time is clearly larger: 4.7 percentage points and +28.21 minutes for boys (+5.1 percentage points and +34.38 minutes for girls).

Nevertheless, given the continuing political controversies surrounding the administrative mechanisms (such as reserved places) used to encourage the educational attainment of Scheduled Castes/Tribe and other disadvantaged children, we note that the schooling of SC/ST children would also benefit from general improvements in school quality and availability – which might be a policy choice with more widespread appeal. If there were no special treatment of SC/ST members, but the local school quality was improved to median standards, the increase in school attendance of 6 to 10 year old SC/ST boys is simulated to be 8.5 percentage points (for girls, 8.2 percentage points). A general policy of school improvement would thus provide, for SC/ST members benefits which would be larger than the improvement to be expected from policy targeted on SC/ST members alone. Of course, a combination of improvement in quality and removal of barriers for SC/ST would lead to much larger improvements for both the general population and the SC/STs.

The results of our Simulation B – which increases the income of all below-median households to the median monthly rural expenditure level – can be summarized as: "little impact – for a very large thought experiment". The small size of the coefficient on income in Table 4 and 5 drives a strong conclusion – that inequality in schooling and human capital investment may play an important role in generating inequality in income, *but not so much the reverse*.[25]

The major message of Table 6 is two-fold: [a] the importance of public policy in the supply of schooling and school quality for current educational choices and [b] the lagged impact of past educational attainment of parents on the current educational choices they make for their children.

For the population as a whole, we estimate the impact of school quality improvements for 6 to 10 year olds to be + 8.1 percentage points in boys' school attendance and +7.4 percentage points for girls. As more students shift into the positive homework time zone, the median human capital investment time would also increase substantially. For the 11 to 14 age group, the school quality impact is estimated at +3.4 percentage points attendance for boys and +5.9 points for girls, and about 32 and 69 more minutes of human capital investment time for boys and girls, respectively.

Our Simulations C and D represent an attempt to model the educational choices of rural Indian families, if they were already starting from the position of all having at least a high school education for the household head and had no problem of female illiteracy, respectively, holding everything else constant. Since most of the household heads are men, Simulation C would mostly affect (in a direct sense) men, whereas Simulation D would affect women. Moreover, Simulation D can be expected to affect the next generation (as compared to Simulation C) because it could mean the presence of an educated daughter or daughter-in-law. Both these simulations show large intergenerational impacts on attendance and human capital accumulation time. For example, for Simulation C, (all heads of household have at least high school) for the 11 to 14 age group, we estimate the school attendance of boys and girls to increase by 10 and 9.1 percentage points, respectively. For Simulation D (all families have at least one literate female adult), the corresponding figures are 4.1 and 6.7 percentage points, respectively. However, while these impacts (including impacts for other age and gender groups) are roughly comparable to or lower than those due to improvements in quality and availability (i.e. Simulation E), the salient question is: how can we change the education of parents?

Our own conclusion from all this is the importance of the supply side of the schooling equation. We conclude that the most relevant and important policy option for increasing attendance and human capital accumulation in rural India is to improve the quality and availability of schooling. This of course does not imply that other policies should not be pursued, particularly in con-

[25] However, as noted above, this result has to be seen in light of the possible measurement error of the expenditure variable.

junction with improvements in quality and availability – and the importance of parental education in influencing the schooling of their children is a reminder that the benefits of more education are received both by today's children and by subsequent generations of children.

6 Conclusions and discussion

This paper has matched state level data on the quality of schooling available in rural India with micro-data on the time use of Indian households. The merged data has been used to estimate models of probability of school attendance and the total time devoted to investment in education. We conclude that more of the inequality in human capital investment time in rural India can be explained by the poor quality and availability of schooling to potential students than can be attributed to parental education, or income, or the barriers of Scheduled Caste and Tribe membership.

We think this finding is important because a very large literature emphasizes the benefits of a more highly educated population. Many studies have concluded that more years of schooling produces higher individual earnings – Temple (2001: 484), for example, concludes that in OECD nations: "the private rate of return to an additional year of schooling is typically between 5 and 15 percent". As well, health and social outcomes, such as the relationship between mother's education and the birth weight of babies in the UK (e.g. Chevalier and O'Sullivan, 2006) or the Height-for-Age of children (e.g. Handa, 1999b; Osberg et al, 2009) have been conclusively linked to education. Wolfe and Haveman have added up the value *to other people* of the changes in health, criminal activity, cognitive development of children, volunteer hours, etc., which are positively associated with increased education and conclude: "a conservative estimate of the value of non-labour market influences is of the same order of magnitude as estimates of the annual marketed, earnings-based of one more year of schooling" (2001:245). Adding together these externalities to others and the private impact of schooling on individual earnings, the aggregate social return to education is a crucial component of economic development.

However, we have to label our findings as "tentative" because of the difficulties of proving causality. Angrist and Krueger (1999) remain a useful example of a large literature in labour economics which stresses the difficulties involved in unambiguous assertions of causality, in non-experimental social science settings. We are not reporting econometric estimates drawn from an environment (like the Progresa experiment in Mexico) in which we can say that the treatments of interest (e.g. school quality, parental education) were randomly assigned in the population. Our results are, strictly speaking, cross-sectional correlations using naturally occurring data which are *consistent with* the hypothesis that variables like local school quality play a causal role in family decisions about human capital investment, but our data cannot reject the hypothesis that other explanations are also possible. Substantively, our results underline the conclusion of Dreze and Sen (2002) on the important – indeed crucial – role of public policy in the human capital formation that is a prerequisite of sustained development. There is really no adequate substitute for good education – and the failure to provide universal access to high quality schooling is a major failure of collective choice in India.

We also hope that we have been able to provide an illustration of the value of time use data, and how it can be used in combination with other data sources, in understanding the development process. Greater investment in schooling and other forms of human capital is but one example of the many structural changes of development that involve decisions about time use within households. These decisions lie outside the domain of market transactions and if analysis of these processes were to be restricted to the use of data on market expenditures, much would be missed. However, because virtually all human activities require time, data on time use – particularly when it is combined using geo-coding with other data on the characteristics of local communities – can often be of great assistance to effective analysis of the development process.

References

AISES (2007a), Seventh All India School Education Survey, Schools, physical and ancillary facilities, New Delhi, National Council for Education Research and Training.

AISES (2007b), Seventh All India School Education Survey, Teachers and their qualifications, New Delhi, National Council for Education Research and Training.

AISES (2007c), Seventh All India School Education Survey, Provisional statistics, New Delhi, National Council for Education Research and Training.

AISES (2007d), Seventh All India School Education Survey, Schooling Facilities in Rural Area, New Delhi, National Council for Education Research and Training.

Angrist, J. D. and A. B. Krueger (1999), Empirical strategies in labor economics, in: Ashenfelter, O. C. and D. Card (eds.), *Handbook of labor economics*, Elsevier, Amsterdam, 1277-1366.

Blanden, J., Gregg, P. and L. Macmillan (2007), Accounting for intergenerational income persistence – Noncognitive skills, ability and education, Discussion Paper No. 2554, Institute for the Study of Labor (IZA), Bonn.

Chatterjee, P. (1993), *The nation and its fragments – Colonial and postcolonial histories*, Princeton University Press, Princeton.

Chevalier, A. and V. O'Sullivan (2006), Mother's education and birth weight, Discussion Paper No. 2640, Institute for the Study of Labor (IZA), Bonn.

Coady, D. P. and S. W. Parker (2004), Cost effectiveness, analysis of demand- and supply side education interventions – The case of progresa in Mexico, in: *Review of Development Economics*, Vol. 8, No. 3, 44-451.

Corak, M. (2006), Do poor children become poor adults? – Lessons from a cross country comparison of generational earnings mobility, Discussion Paper No. 1993, Institute for the Study of Labor (IZA), Bonn.

Corak, M. (2004), Generational income mobility in North America and Europe – An introduction, in: M. Corak (ed.), *Generational income in North America and Europe*, Cambridge University Press, Cambridge.

Deaton, A. (1999), *The analysis of household surveys – A microeconometric approach to development policy*, Johns Hopkins University Press, Baltimore.

Dreze, J. and G. Kingdon (2001), School participation in rural India, in: *Review of Development Economics*, Vol. 5, No. 1, 1-24.

Dreze, J. and A. K. Sen (2002), *India – Development and participation*, Oxford University Press, New York.

Gupta, D. (1993), *Social stratification*, Oxford University Press, New Delhi.

Handa, S. (1999), Maternal education and child height, in: *Economic Development and Cultural Change*, Vol. 47, No. 2, 4-21.

Hanushek, E., Lavy, V. and K. Hitomi (2006), Do students care about school quality? – Determinants of dropout behavior in developing countries, Working Paper No. 12737, National Bureau of Economic Research, Cambridge, MA.

Heckman, J. J. (1979), Sample selection bias as a specification error, in: *Econometrica*, Vol. 47, No. 1, 153-162.

Hirway, I. (2000), Tabulation and analysis of the Indian time use survey data for improving measurement of paid and unpaid work, Expert Group Meeting on Methods for conducting time use surveys, 23-27 October 2000, New York, United Nations Secretariat, Statistics Division ESA/STAT/AC.79/20.

Indian Time Use Survey (ITUS) (1998), Instruction manual for field staff, Central Statistical Organization, Ministry of Statistics, Planning and Programme Implementation, New Delhi.

Indian Meteorological Department (IMD) (2011), Climate profile of India, available at : www.imd.gov.in/doc /climateprofile.pdf.

Jäntti, M., Bratsberg, B., Röed, K., Raaum, O., Naylor, R., Österbacka, E., Björklund, A. and T. Eriksson (2006), American exceptionalism in a new light – A comparison of intergenerational earnings mobility in the nordic countries, the United Kingdom and the United States, Discussion Paper No. 1938, Institute for the Study of Labor (IZA), Bonn.

Motiram, S. and L. Osberg (2010a), Social capital and basic goods – The cautionary tale of drinking water in India, in: *Economic Development and Cultural Change*, Vol. 59, No. 1, 63-94.

Motiram, S. and L. Osberg (2010b), Gender inequalities in tasks and instruction opportunities within Indian families, in: *Feminist Economics*, Vol. 16, No. 3, 141-167.

National Sample Survey Organization (NSSO) (2000), Migration in India – 1999-2000, Central Statistical Organization, Ministry of Statistics, Planning and Programme Implementation, New Delhi.

Osberg, L., Shao, J. and K. Xu (2006), The growth of poor children in China 1991-2000 – Why food subsidies may matter, in: *Health Economics,* Vol. 18, No. 1, 89-108.

Public Report on Basic Education in India (PROBE) (1999), Oxford University Press, New Delhi.

Temple, J. (2001), Growth effects of education and social capital in the OECD Countries, in: J. Helliwell (ed.), *The contribution of human and social capital to sustained economic growth and well being*, International Symposium Report, Paris and Ottawa, Organization for Economic Cooperation and Development and Human Resource Development Canada, 461-501.

Tiebout, C. M. (1956), A pure theory of local expenditures, in: *Journal of Political Economy*, Vol. 64, No. 5, 416-424.

Wilson, K., Smeeding, T., Miller, L. and R. Haveman (2007), *Higher education and social mobility in the United States – A glimpse inside the black box?* Prepared for the Russell Sage Foundation Meetings in January 2007, Los Angeles.

Wolfe, B. and R. Haveman (2001), Accounting for the social and non-market benefits of education in: J. Helliwell (ed.), *The contribution of human and social capital to sustained economic growth and well being*, International Symposium Report, Paris and Ottawa, Organization for Economic Cooperation and Development and Human Resource Development Canada, 461-501.