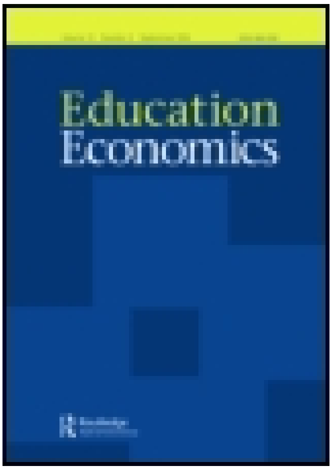

Education Economics
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/cede20

Do returns to education matter to schooling participation? Evidence from India

Geeta Gandhi Kingdon [a] & Nicolas Theopold [a]
[a] Institute of Education , University of London , UK
Published online: 31 Oct 2008.

Education Economics
Vol. 16, No. 4, December 2008, 329–350

Do returns to education matter to schooling participation? Evidence from India

Geeta Gandhi Kingdon* and Nicolas Theopold

Institute of Education, University of London, UK

While it might be expected that demand for schooling will depend positively on the economic returns to education (ER) in the local labor market, in fact there is theoretical ambiguity about the sign of the schooling–ER relationship when households are liquidity-constrained. Whether the relationship is positive or negative depends on which effect dominates – the positive substitution effect of an increase in ER on years of education, or the negative income effect. For India, we find a positive relationship between the rate of return to education for adults in the local labor market and school attainment of girls and non-poor boys. The size of the effect of ER on years of education acquired is large for some groups. However, for poor boys the negative income effect dominates the positive substitution effect. Thus, while improved economic incentives for acquiring education have a positive impact on educational attainment of girls and non-poor boys, they worsen the educational attainment of poor boys. Policy implications are discussed.

Keywords: schooling attainment; market returns to education; child labor; India

1. Introduction

Much work in education economics focuses on explaining the educational decisions of individuals. How much education to acquire entails a comparison of the cost and benefits of each extra year of education. Demand for education is hypothesized to rise with the benefits of education and to fall with its costs. There is much analysis of the role of supply-side measures in reducing the *costs* of school participation; for example, reduction of school fees, direct cash subsidies, school-construction programs to reduce travel costs and the provision of non-monetary benefits in schools, such as school meals (Kremer and Chen 2002; Schultz 2004; Drèze and Kingdon 2001; Duflo 2001; Vermeersch 2004). The efficacy of supply-side measures in improving the quality of schooling, in order to increase the *benefits* of education, has also been analyzed. For instance, much research focuses on the effect of class size on pupil achievement and on school participation (Angrist and Lavy 1999; Krueger 1999; Case and Deaton 1999; Hanushek 2003; Drèze and Kingdon 2001). Arguably, one the most powerful determinants of the demand for schooling is its expected *economic* benefits and it is an interesting research and policy question whether and how much the expected economic return to schooling affects individuals' demand for it. This question is particularly important in less developed countries where compulsory education laws either do not exist or are not enforced, and sizeable sections of the child population do not participate in schooling. Moreover, if the economic incentives for acquiring schooling are particularly low for certain

*Corresponding author. Email: g.kingdon@ioe.ac.uk

ISSN 0964-5292 print/ISSN 1469-5782 online

DOI: 10.1080/09645290802312453
http://www.informaworld.com

groups (e.g. women or low-caste persons), this may explain the persistence of large gender and caste gaps in schooling level.

In general, it is intuitive to think that demand for schooling will increase with the economic return to education. However, liquidity constraints may change this positive relationship into a negative one since for credit-constrained poor households the negative income effect may dominate the positive substitution effect (of higher returns to education) on demand for schooling. This may be because higher economic returns to education make children's current schooling more valuable in the labor market and thus may cause a poor family to withdraw children from school and put them to work. If so, then an increase in returns to education could lead to unintended perverse effects on the schooling of poor children.

However, there is relatively little testing of the role played by economic returns to education in the determination of schooling participation, and of whether the role differs for poor and non-poor households. Some studies include regional measures of monetary returns in explaining schooling participation, such as the proportion of employment in local industry (Tansel 2002; Gungor 2001), but some papers use returns to education in the local labor market to explain children's participation in education – Yamauchi-Kawana (1997), Gormly and Swinnerton (2003), and going back in time, Freeman (1975) and Soumelis (1981). The object of the current paper is to ask, using data from India, whether and how much local economic returns to education, as measured by the Mincer earnings function, influence educational decisions, and whether they do so differently for liquidity-constrained and non liquidity-constrained households.

The paper is structured as follows. Section 2 outlines a theoretical model. Section 3 describes the estimation approach. The data are discussed in Section 4. Section 5 discusses results and Section 6 concludes.

2. Theoretical and estimation issues

The present paper is concerned with testing the effect of adult returns to education on the schooling of children and adolescents. The theoretical grounding for this comes from an adaptation of Baland and Robinson (2000). Gormly and Swinnerton (2003) extend this model to create a theoretical framework of the influence of returns to education on educational outcomes at the individual level.[1]

In this two-period model, families live together in Period 1, and children maintain their own households in Period 2. Parents are assumed to be altruistic towards their children, meaning that they derive utility from their n children's utility, but children are selfish, precluding any transfers from children to parents in Period 2. c_1 and c_2 are the parents' consumption in Periods 1 and 2 and c_c is each adult–child's consumption. Hence parents optimize over:

- $u(c_1)$, parents' utility from household consumption in $t = 1$;
- $u(c_2)$, parents' utility from consumption in $t = 2$;
- $\delta n v(c_c)$, parents' utility from children's consumption in period 2.

δ, parents' degree of altruism towards their children, and $u(c_1)$, $u(c_2)$ and $v(c_c)$ are increasing and concave in their arguments. Parents' incomes are fixed at a_1. Parents allocate each child's time to two activities, school (e) and work ($1 - e$), work being compensated at wage unity. Household consumption in Period 1 is constrained by parental income a_1, the total of the n children's income $n(1 - e)$, less the amount that parents save for Period 2 (i.e. s). Parents' second-period consumption equals their income a_2, plus savings s, less any bequest they make to their children, b. Each child's Period 2 (adulthood) income is determined by:

- e, the amount of education they received;
- b, bequests from their parents;
- θ, the return to education, which is exogenous.

An adult child's wage is equivalent to a human-capital production function, $h(e,\theta)$, which is increasing and concave in its arguments. Gormly and Swinnerton (2003) provide the necessary conditions for closure of the model in more detail.

An important condition of the model is that individuals are not able to borrow to smooth their consumption between time periods, meaning that the household saving rate must be $s \geq 0$. Poor households may thus be liquidity constrained in situations where they would like to borrow to increase Period 1 consumption. This yields the household optimization problem:[2]

$$\max_{(s,e,b)}\Big[u\big(a_1 + n(1-e) - s\big) + u\big(a_2 + s - nb\big) + \delta n v\big(h(e;\theta) + b\big)\Big] s.t.\ s \geq 0; b \geq 0 \qquad (1)$$

It is shown that if households are not liquidity constrained (i.e. if households do not need to borrow to increase their consumption in Period 1), investments in education are socially optimal and that $h_1(e;\theta) = 1$. Also, the relationship between returns to education (θ) and the amount of education acquired is shown to be:

$$\frac{\partial e}{\partial \theta} = -\frac{h_{12}}{h_{11}} \qquad (2)$$

For instance, if education and good adult labor market conditions or school quality are complements in the production of higher levels of human capital and therefore of higher wages (which is a plausible), then Equation (2) implies that $\partial e/\partial \theta > 0$; that is, education increases with improvement in either of the two factors.

The $\partial e/\partial \theta$ term is positive if the liquidity constraint does not bind. However, if the liquidity constraint is binding, Gormly and Swinnerton show that:

$$\frac{\partial e}{\partial \theta} = -\frac{\delta n\Big[h_{12}\big(e;\theta\big)v'\big(c_c\big) + h_1\big(e;\theta\big)h_2\big(e;\theta\big)v''\big(c_c\big)\Big]}{\nabla} \qquad (3)$$

where $\nabla < 0$ is the second-order condition for e from Equation (1).

The parental altruism assumption of the above theoretical model can be challenged on the grounds that it ascribes myopia to parents: if children are selfish and do not transfer any income or wealth to parents in their old age, parents will find this out over time, and discount their altruism and not send their children to study but rather send them to work at a young age. In a game theoretic framework, the advantageous position enjoyed by children can quickly dissipate. The parental altruism assumption might also be challenged in societies with no social security where parents rely on old-age support from children and where altruism may thus not be a driver of parental decisions about children's schooling versus work. However, while the above model is necessarily a simplification of reality, the parental altruism assumption has some empirical support (Schluter and Wahba 2004; Bhalotra 2004) and has also been incorporated in many previous studies either implicitly (for example, Attanasio, Meghir, and Santiago 2005; Todd and Wolpin 2003) or explicitly (Gormly and Swinnerton 2003; Baland and Robinson 2000).

In a liquidity-constrained environment, two opposing effects influence schooling decisions: if returns to education increase, there is a substitution effect towards education instead of work, driven by relatively higher profitability of schooling *vis-à-vis* current work by children. However, there is also an income effect at play, due to increased lifetime earnings encouraging increased present consumption. If liquidity-constrained parents cannot borrow to increase consumption today and cannot alter their own earnings, a consequence will be a negative effect on schooling of their children: they may choose to let their children work more to benefit in Period 1 from increased lifetime incomes associated with the now higher return (more profitable) education.

Hence, in unconstrained households, the relationship between returns to education and schooling participation is expected to be positive. In liquidity-constrained households, this relationship is expected to be smaller in magnitude (or even negative), and the extent to which it will be smaller will depend on the relative sizes of the substitution and income effects.

It is noteworthy that the relationship described above only holds at the household level. At the aggregate economy level, we expect the supply of labor to influence the relationship between educational attainment and educational returns. Duflo (2001) writes an equation relating the returns to education to the supply of educated labor:

$$b_{jk} = 2\beta_1 S_j + 2\beta_2 \overline{S} + \beta_3 q_{jk} + v_j \tag{4}$$

Here, b_{jk} represents the return to education of people from cohort k in region j, S_j the average years of schooling in the individual's region, $\overline{S}$ the average years of schooling in the country, and q_{jk} is a quality index.

Since an increase in average education is likely to reduce the returns to education, due to supply-side effects, we expect that regions with high levels of education could experience lower returns to education due to a relatively higher supply of skilled labor. However, general equilibrium effects may negate such a phenomenon, if the supply of educated labor affects endogenous technical change, and thus affects demand for skilled labor. Foster and Rosenzweig (1996) note the possibility of increased endogenous growth due to a highly educated labor force. Papers by Nelson and Phelps (1966), Schultz (1975) and Gemmell (1996) put forward the view that high levels of education will enhance growth, and this could instigate a positive relationship between supply of educated persons and returns to education. Krueger and Lindahl (2001) and Temple (2001) explain the failure of other studies to find a positive relationship between education and economic growth in cross-country regressions, and they find that when measurement error and outliers are taken account of, education does increase growth. Nevertheless, we remain agnostic on the precise relationship between education and growth, and thus on the expected relationship between a region's educational attainment and its returns to education. The possibility remains that, in an educational attainment function, the educational return variable will suffer from simultaneity bias; that is, it will be jointly determined with educational attainment.

Another problem is that the schooling attainment equation may suffer from omitted variable bias, which (like joint determination) is another source of endogeneity bias. Both educational returns (θ, henceforth *ER*) in the local labor market and educational attainment (henceforth *EDYRS*) may be driven by some third unobserved factor such as unmeasured regional characteristics that are in the error term of the estimated schooling equation. For instance, in regions that are progressive for historical reasons, both *EDYRS* will be high and *ER* may also be high if such regions attract inward investment that raises the return to education in the local labor market.

In this paper, we attempt to deal with both forms of endogeneity bias; namely, simultaneity bias and omitted variable bias.

3. Data description

The present paper draws on data from two household surveys conducted by the National Sample Survey Organization of India: the 50th and the 55th rounds, dating from 1993–1994 and 1999–2000, respectively. They are abbreviated with 1993 and 1999, respectively, for convenience. Both rounds have employment and unemployment as their topic (NSS 1993, 1999).

Each of the rounds contains information on approximately 100,000 households covering all Indian states and subregions. The information contained in these two data-sets overlaps to a large extent. The data include information relating to demographic factors, education, employment and earnings, and household-level information relating to social status, expenditure, principal household activity and related information.

For the measurement of the educational return (*ER*), three variables are of particular importance and are their structure of interest: wages, hours worked and the years of education attained.

Wages are recorded in monetary units for both cash and kind income, and added together to form a total. In the questionnaires, the recall period for waged earnings is one week. Hours worked are inferred from weekly activity reports. Respondents were asked to detail the time spent in different activities over the past week. Responses were recorded in half-day units. We assume that each half-day worked represents four hours of work.[3] We employ a simple transformation to infer the number of hours worked, if the activity reported led to wage earnings:

$$\text{Hours worked last week} = (\text{Number of half days reported}) \times 4 \tag{5}$$

Mincerian earnings functions take years of education as the measure of human capital accumulated. In the NSS samples, however, educational attainment is not recorded by years of education, but rather by level of education completed. Conversion from educational attainment categories to years of education is detailed in Table 1.

Clearly, in this context educational attainment only serves as a proxy measure for the years of education completed. It does not take into account any repeats. This, however, is not problematic in the context, as, arguably, the education level completed captures more accurately the level of human capital accumulated than a direct measure of years spent in schooling. This view is directly supported by the human capital hypothesis.

A second limitation associated with this method of conversion is the fact that high levels of education, such as postgraduate or doctoral studies, cannot be recorded. This implies a potential over-estimation of the returns of education, as high earnings associated with very high levels of education are effectively attributed to lower educational attainment.

Table 1. Transformation of education coding to years of education.

Educational attainment code	Imputed years of education
Not literate	0
Literate through attending NFEC/AEC, TLC or others	1
Literate, but below primary	3
Primary	5
Middle	8
Secondary	10
Higher secondary	12
Graduate and above	15

Note: NFEC, non-formal education centre; TLC, Total Literacy Campaign; AEC, alternative education centre.

Each Indian state is subdivided into two, three or four regions (known as 'state-regions') based on similarity of agro-climatic conditions. Each state-region contains several districts. There are 78 state-regions in India and the state-region is taken as the relevant geographical unit representing the local labor market for which the rate of return to education is calculated. As there is likely to be much more inter-district than inter-state-region migration, it is a more natural unit for 'local' labour market. It is also easy to match state-regions from the 1993 and 1999 waves of NSS data.[4]

Table 2 defines the variables used in the estimation. Per-capita household expenditure (*pce*) and wages earned have all been deflated to 1995 prices for comparability, using Consumer Price Index (CPI) information from the World Development Indicators (World Bank 2003). Seventy-seven different state-regions are contained in the sample. With regards to religion dummies, Hinduism has been chosen as the base category, due to its high prevalence in India. As to the social group variables, the base category comprises persons not belonging to the 'scheduled caste' or 'scheduled tribe' categories. An overview of summary statistics from the two data-sets is presented in Table 3.

As can be seen from Table 3, both data-sets are approximately the same size, with more than 560,000 individuals. The age distribution and proportion of wage workers is also fairly similar in both samples.[5] Mean levels of education have increased from 1993 to 1999, irrespective of the chosen decomposition of the data-set. Wage earners have, on average, more than a year of education greater than those not earning a wage. Approximately one-third of the sample resides in urban areas, although this number increases slightly between the two surveys; relatively more wage activity takes place in urban areas.

Women are under-represented among wage earners and attain lower levels of education. Especially at low levels of per-capita expenditure (bottom decile), there is a notable gap in average educational attainment between females and males, although the size of this gender gap has fallen substantially over time: in 1993, the education attainment gap between the genders was about 0.95 years of education, which reduced to 0.58 years by 1999. At high expenditure levels (top decile), however, this gender gap is much smaller – with 0.26 years in 1993 and a reversal to women attaining 0.09 more years of education by 1999. These results are a useful starting point for the gender-based results presented in Section 4.

Real wages increased by approximately 15% between the two time periods. However, real per-capita household expenditure decreased slightly between the years, owing to an increase in average household size between the years. Lastly, the demographic composition of the sample is very similar between the two surveys.

Table 2. Variables used in the estimation.

Variable	Abbreviation	Definition
Personal		
AGE	a	Age of individual in years
AGESQ	a^2	Square of AGE
AGE5 to AGE20	–	Dummy variable for each age
EDYRS	e	Number of years of education, as defined in Table 1
LN-WAGES	w	ln(weekly total wage)
HOURS	hr	Hours worked, as defined in Equation (5)
AGE_i	a_i	Dummy variable for age i
FEMALE	f	Gender dummy: male = 0, female = 1
MARRIED	m	Marital status dummy: never married = 0; married, divorced, widowed = 1
Demographic		
HH-EDUC	he	*EDYRS* of the designated head of household
HH-EXP	pce	Household per-capita expenditure over the past month
CHILD-10	$ch10$	Number of children aged 10 years or younger in the household
NUM-65	$num65$	Number of individuals aged 65 years or older in the household
LAND-OWN	lo	Dummy: household owns land = 1, does not own land = 0
SR_i	sr_i	Regional dummy: state-region
$SR_i'e$	$sr_i'e$	State-region and *EDYRS* interaction variable
URBAN	ur	Location dummy: rural = 0, urban = 1
*REL-**	rel_i	Religion dummies:
		Muslim, Christian, Sikh, Jainist, Buddhist
		Hinduism omitted as base category
SCH-TRIBE	st	Scheduled tribe dummy
SCH-CASTE	sc	Scheduled caste dummy
Calculated		
ER	er	Local rate of return to education in the state-region (education coefficient as calculated by our estimation of Equation (6))

4. Estimation and results

Estimation of the influence of Mincerian returns on schooling participation is carried out in a two-stage process. In the first stage, regional rates of returns to education (*ER*) are estimated using Mincerian earnings functions.[6] The second stage comprises individual-level estimation, as well as aggregate (state-region-level) estimation, of educational attainment for age (*EDYRS*). Key to the analysis is the high degree of heterogeneity in educational attainment in different regions of India.

4.1. *'First-stage' earnings function estimation*

In the first stage, an earnings equation is estimated. The Mincer specification, as outlined previously, is used as follows:

Table 3. Summary statistics for the NSS data-sets.

	NSS 1993		NSS 1999	
Variable	*n* or mean	SD	*n* or mean	SD
Size of data-set				
Individuals in data-set	564,695		588,525	
Wage earners aged 21 years or older	73,753		86,251	
Mean education levels (years) for different groups				
Whole sample	3.880	(4.35)	4.358	(4.54)
Persons aged 21 years and above	4.428	(4.89)	5.121	(5.13)
Wage earners aged 21 years and above	5.824	(5.49)	6.345	(5.47)
Persons aged 21 years and above not earning a wage	4.067	(4.66)	4.702	(4.94)
Persons aged 5–20 years	4.105	(3.42)	4.345	(3.42)
Females aged 5–20 years, bottom 10%[a]	1.609	(2.39)	2.142	(2.58)
Males aged 5–20 years, bottom 10%[a]	2.556	(2.79)	2.726	(2.78)
Females aged 5–20 years, top 10%[a]	6.086	(3.75)	6.784	(3.73)
Males aged 5–20 years, top 10%[a]	6.344	(3.62)	6.718	(3.61)
Demographic				
Percentage living in urban areas	35.9%		38.1%	
Percentage of females in the sample	47.2%		47.4%	
Female share of wage earners	22.8%		22.5%	
Urban share of wage earners	46.9%		48.8%	
Share of Hindus in sample	78.1%		77.4%	
Share of Muslims in sample	11.2%		12.6%	
Share of Christians in sample	6.0%		5.1%	
Share of Sikhs in sample	2.3%		2.5%	
Share of Jains in sample	0.3%		0.4%	
Share of scheduled tribe persons in sample	11.1%		11.4%	
Share of scheduled caste persons in sample	14.8%		16.2%	
Economic				
Household per-capita expenditure – monthly	457.6	(529.2)	438.9	(358.1)
Average weekly wage earned (1995 prices)	348.5	(412.5)	400.8	(891.3)
Returns to education for wage earners (*ER*) (estimated for persons aged 21 years or older)	7.81%	(1.90%)	8.34%	(1.46%)

Source: Authors' own calculations from NSS 1993 and 1999 data.
Note: Per-capita household expenditure and average weekly wages have been deflated to 1995 prices. [a]Top or bottom 10th percentile in the distribution of household per-capita expenditure.

$$w_{ij} = \alpha + \beta X_i + \gamma Y_i + \sum_{j=2}^{j=77} \delta_j sr_j + \sum_{j=2}^{j=77} \beta_{sr_j \times e_i} sr_j \times e_i + \beta_e e_i + \varepsilon_{ij}$$

where i is the index for the individual, and j is the index for the state-region. X is a vector of individual characteristics, Y a vector of social and demographic characteristics, e is years of education, sr_j is a dummy variable for the state-region and $sr_j \times e_i$ is an interaction term of the years of education and the state-region dummy variable (sr). Table 2 defines the variables used.

The use of state-region dummies, (sr_j), and of the interaction variable between state-region and educational attainment, ($sr_j \times e_i$), allows calculation of state-regional returns to education:

$$er_1 = \beta_e \text{ for state region } j = 1$$
$$er_j = \beta_e + \beta_{sr_j \times e} \text{ for } 2 <= j <= 77$$

Whilst the variation in *ER* is driven by differences in the slope of the earnings function, as recorded by the sum of β_e and $\beta_{srj \times e}$, the inclusion of state-region dummies is also important: it controls for differences in the intercept of the earnings function (i.e. for differences in wage *levels* across state-regions).

Estimation including the state-region variables and their interaction generates a regression function with 166 explanatory variables. The size of the data-sets makes this viable, with about 60,000 wage earners of age 21 and above in each year's sample (see Tables 4 and 5).

A source of concern in earnings function estimation is that of sample selectivity bias: the sample of people earning a wage may not be a random draw from the adult population. Using variables that determine participation of a person in the waged labor force but do not influence the conditional level of wages, a selection equation is estimated and its results used to correct the estimation of the earnings function (Heckman 1979). The binary selection variable 'wage earner' (or *we*) takes value zero if an individual is not earning a wage and value one if he/she is earning a wage.

The credibility of the Heckman procedure depends on the extent to which good identifying variables are available that can be excluded from the wage equation but affect selection into waged work. The data-sets yield three variables that may explain participation in the waged labor force, but not affect wages conditional on being in the labor force: *LAND-OWNER*, *NUM-65* and *CHILD-10* – see Schultz (1990) and Tansel (1994), who use land and unearned income as valid exclusion restrictions. Household demographic characteristics, such as the number of elderly aged 65 and above (*NUM-65*), and number of child dependants (*CHILD-10*), are likely to play a role in individuals' choice about labor force participation and type of employment undertaken. For instance, in households with a large number of dependants, working-age adults (especially women) are more likely to seek and accept flexible forms of work, such as self-employment, informal or casual employment rather than wage work. Similarly, land ownership (*LAND-OWNER*) is likely to be associated with lower likelihood of seeking wage employment. Hence, the first-stage selection equation contains all wage equation variables (except hours worked) and the three exclusion restrictions outlined above. We expect negative signs on *LAND-OWN*, *NUM-65* and *CHILD-10*.

The sample of earners in the wage equation is limited to ages 21 and above. This precludes overlap between the observations included in earnings function calculation and those included in educational attainment functions to be estimated in the second stage.

Detailed estimation results are presented in Tables 4 and 5. Both estimations are adjusted for cluster effects at the village level and use heteroscedasticity-robust estimators, as this proved an issue in preliminary estimations. Results for the robust estimators can be considered efficient due to the large sample sizes in both time periods.

The variables used in the first-stage probit for identifying the selectivity term, λ, are *LAND-OWNER*, *NUM-65* and *CHILD-10*. They are valid exclusion restrictions, as they show strong association with selection into waged work and are theoretically justified above. λ is significant at the 1% level in the earnings functions for both years in Tables 4 and 5.

Table 4. Wage function: 1993 sample.

	OLS	Heckman correction	
Variable	Wage function	Wage function	Equation for selection into waged work
EDYRS	0.0824***	0.0822***	−0.0009
	(22.27)	(28.34)	(−0.30)
HOURS	0.0324***	0.0324***	–
	(81.00)	(162.00)	–
AGE	0.0555***	0.0477***	0.0867***
	(26.43)	(20.74)	(57.80)
AGESQ	−0.0006***	−0.0005***	−0.0011***
	(−30.00)	(−28.02)	(−20.03)
FEMALE	−0.3157***	−0.2445***	−0.8333***
	(−38.98)	(−16.19)	(−143.67)
URBAN	0.2226***	0.1971***	0.1912***
	(18.10)	(24.04)	(29.88)
MARRIED	0.1666***	0.1594***	0.1431***
	(13.54)	(15.33)	(14.60)
REL-MUSL	−0.0231	−0.0176	−0.0387***
	(−1.38)	(−1.61)	(−4.03)
REL-CHRIST	0.0190	0.0107	0.1166***
	(0.81)	(0.70)	(7.72)
REL-SIKH	0.0615*	0.0741***	−0.1314***
	(1.82)	(2.72)	(−5.39)
REL-JAIN	0.0650	0.1197**	−0.6523***
	(0.85)	(2.10)	(−14.53)
REL-BUDDH	−0.0191	−0.0427	0.3268***
	(−0.60)	(−1.50)	(11.43)
SCH-TRIBE	−0.0385*	−0.0571***	0.2323***
	(−1.92)	(−4.57)	(20.93)
SCH-CASTE	−0.0447***	−0.0829***	0.4846***
	(−3.41)	(−7.82)	(64.61)
LAND-OWNER			−0.3776***
			(−49.68)
NUM-65			−0.0926***
			(−20.58)
CHILD-10			−0.0632***
			(−33.26)
Intercept	1.9348***	2.214***	−1.7454***
	(40.48)	(34.17)	(−51.64)
λ		−0.114***	
		(−5.35)	
n	73,753	73,753	358,276
R^2	0.5421		

Note: t-values are in parentheses below the coefficients. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

Table 5. Wage function: 1999 sample.

	OLS	Heckman correction	
Variable	Wage function	Wage function	Equation for selection into waged work
EDYRS	0.0774***	0.0776***	−0.0057*
	(18.43)	(35.27)	(−1.97)
HOURS	0.0352***	0.0352***	–
	(176.00)	(352.00)	–
AGE	0.0645***	0.0578***	0.0980***
	(40.31)	(32.11)	(65.33)
AGESQ	−0.0006***	−0.0001***	−0.0010***
	(−12.68)	(−10.92)	(−14.03)
FEMALE	−0.2900***	−0.2300***	−0.9400***
	(−38.82)	(−18.15)	(−164.91)
URBAN	0.2261***	0.2100***	0.1040***
	(26.29)	(36.84)	(16.00)
MARRIED	0.1724***	0.1675***	0.1160***
	(17.24)	(22.64)	(12.21)
REL-MUSL	−0.0152	−0.0080	−0.0840***
	(−1.35)	(−1.03)	(−9.03)
REL-CHRIST	0.0392**	0.0347***	0.0580***
	(2.35)	(3.04)	(3.79)
REL-SIKH	0.0804***	0.0952***	−0.1830***
	(3.02)	(5.04)	(−8.06)
REL-JAIN	0.1417**	0.1830***	−0.6550***
	(2.04)	(4.24)	(−14.69)
REL-BUDDH	0.0127	0.0173	−0.0740**
	(0.38)	(0.82)	(−2.64)
SCH-TRIBE	−0.0051	−0.0184**	0.2230***
	(−0.44)	(−2.09)	(21.04)
SCH-CASTE	−0.0127	−0.0404***	0.4490***
	(−1.59)	(−5.32)	(64.14)
LAND-OWNER			−0.3591***
			(−52.04)
NUM-65			−0.0808***
			(−20.2)
CHILD-10			−0.0457***
			(−28.56)
Intercept	1.7194***	1.9390***	−1.7517***
	(4.54)	(38.86)	(−51.22)
λ		−0.0920***	
		(−5.51)	
n	86,251	86,251	338,129
R^2	0.6707		

Note: t-values are in parentheses below the coefficients. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

In the first-stage probit of wage work participation, all coefficients exhibit the expected signs except those on the dummy variables for low caste (scheduled caste and scheduled tribe). A possible explanation is that members of scheduled castes and tribes are less likely to have capital to start self-employment, thus explaining the higher likelihood of low-caste members to be wage earners.

An inspection of the coefficients of the earnings functions shows that there is relatively little difference between selectivity-bias corrected and ordinary least squares (OLS) estimates. This fact is also confirmed by results in Table 6, which summarizes the estimated returns to education *ER*. This shows that, in each year, the two competing specifications show very little difference in mean and extreme values of *ER*. Consequently, we choose OLS results for further analysis since that is the more standard estimation model and lends itself more conveniently to the use of statistical techniques such as the instrumental variables we utilize later in the paper. The estimated rate of return to education is very similar to those in other studies for India.[7]

Earnings function results presented in Tables 4 and 5 omit the coefficients for the 77 state-region variables and the 77 interaction variables for space reasons. The coefficient of ER reported here is that for State-region 21, the dry areas of Gujarat (the base category). Its value is not representative for mean returns to education in India. R^2 values of the OLS earnings functions are reassuring, with values of 0.54 for the 1993 data-set and 0.67 for the 1999 data-set. Also, except for the Buddhist religion dummy, coefficients exhibit highly significant *t*-values.

In the OLS earnings functions, all variables exhibit expected signs. The age–earnings relationship derived from *AGE* and *AGESQ* predicts earnings to peak at the age of 50 in 1993 and at the age of 52 in 1999, *ceteris paribus*. This conforms to human capital theories of increased productivity due to experience being offset by age-driven productivity losses later in life. Female wage disadvantage stands at around 30%, but decreases between the two time periods. Marital status and urban location show strong association with wages earned, again conforming with expected magnitudes and directions. Lastly, the data suggest that caste discrimination in waged work is still an issue, although wage losses associated with belonging to a scheduled caste or tribe decrease considerably between the years.

4.2. 'Second-stage' estimation of educational attainment

In the second stage of the estimation process, the effect of educational returns on schooling attainment (years of education, *EDYRS*) is estimated: firstly, individual schooling attainment functions are estimated; and secondly, state-region level average schooling attainment functions are estimated, to aggregate results at the level of the regional labor markets.

Table 6. Summary of the returns to education coefficient under different specifications of the wage function, from Tables 4 and 5.

Data-set	Specification	Mean (%)	Minimum (%)	Maximum (%)
1993	Heckman	7.65	2.68	11.44
1993	OLS	7.81	2.82	11.49
1999	Heckman	8.34	4.57	12.10
1999	OLS	8.34	5.18	11.93

4.1.1. Individual-level analysis

The first and most intuitive way to estimate educational attainment (*EDYRS*) functions is at the individual level. For this, the sample is limited to persons aged 5–20 years old – this choice of sample being driven by the fact that schooling participation occurs mainly between ages five and 20 (the sample of individuals aged 21 years and older had been used in Tables 4 and 5 for the estimation of wage functions). We include separate dummy variables for each age from six to 20 years, which effectively means we are modeling years of schooling (*EDYRS*) for age, as in Case and Deaton (1999), who also examine the determinants of educational attainment. The dummy for age five is the base category for age.

The first two columns of Table 7 present our individual-level educational attainment functions, using the 1999 NSS data. The equations contain a dummy variable for gender and several control variables, including household per-capita expenditure (*pce*). While the coefficient on *pce* may suffer from endogeneity bias,[8] the data do not yield an instrument of acceptable quality for *pce*. However, this should not impact our analysis in a central way as the focus here is on the effect of education returns (*ER*) on schooling attainment, and because *pce* and *ER* are unlikely to be highly correlated. Estimates at the individual level are conducted using a cluster-robust estimator since *ER* is aggregated at the level of the state-region 'cluster'.

Table 7. Educational attainment functions: full sample results.

	Individual-level		State-region-level		
	1999 data	1999 data	Pooled 1993 and 1999 data		1999 data
Variable	OLS	IV[a]	OLS	Fixed effects	IV[a]
ER	4.7100***	2.6764*	−2.9398	−3.1700	2.1742
	(5.36)	(1.88)	(1.48)	(1.27)	(0.31)
FEMALE	−0.4255***	−0.4252***	4.2873**	−2.7361	1.9540
	(31.60)	(31.59)	(2.61)	(1.43)	(0.60)
URBAN	0.5473***	0.5486***	−0.0189	0.1850	0.0688
	(18.62)	(18.64)	(0.06)	(0.32)	(0.14)
HH-EXP	0.0010***	0.0010***	−0.0000	−0.0005	0.0005
	(8.07)	(8.03)	(0.08)	(0.75)	(0.62)
HH-EDUC	0.1564***	0.1565***	0.4204***	0.3954***	0.2655***
	(51.71)	(51.80)	(10.08)	(11.31)	(3.22)
SCH-TRIBE	−0.6510***	−0.6352***			
	(14.54)	(13.81)			
SCH-CASTE	−0.5709***	−0.5726***			
	(20.44)	(20.43)			
AGE6	0.7137***	0.7145***			
	(37.53)	(37.58)			
AGE7	1.1739***	1.1748***			
	(59.77)	(59.78)			
AGE8	1.3662***	1.3672***			
	(74.45)	(74.48)			
AGE9	1.5601***	1.5618***			
	(74.77)	(74.88)			

Table 7. *(Continued)*.

	Individual-level		State-region-level		
	1999 data	1999 data	Pooled 1993 and 1999 data		1999 data
Variable	OLS	IV[a]	OLS	Fixed effects	IV[a]
AGE10	1.9197***	1.9210***			
	(96.64)	(96.63)			
AGE11	2.4787***	2.4804***			
	(103.25)	(103.26)			
AGE12	2.7739***	2.7754***			
	(118.14)	(118.06)			
AGE13	3.6040***	3.6050***			
	(122.92)	(122.96)			
AGE14	4.0823***	4.0841***			
	(130.74)	(130.65)			
AGE15	4.4084***	4.4092***			
	(127.92)	(127.92)			
AGE16	4.9538***	4.9550***			
	(132.12)	(132.10)			
AGE17	5.6633***	5.6641***			
	(134.68)	(134.68)			
AGE18	5.1922***	5.1936***			
	(129.26)	(129.25)			
AGE19	5.8428***	5.8439***			
	(117.44)	(117.51)			
AGE20	4.9675***	4.9687***			
	(110.05)	(110.07)			
AGE			1.0243***	0.3460***	1.1805***
			(8.24)	(3.50)	(9.05)
Constant	−0.1335	0.0368	−12.3079***	−0.2515	−12.8935***
	(1.55)	(0.28)	(8.47)	(0.15)	(7.69)
n	217834	217834	154	154	77
R^2	0.44	0.44	0.81	0.67	0.82

Notes: Dependent variable is *EDYRS* (years of education). Robust *t*-statistics in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. [a]In IV equations, ER_{1999} is instrumented with ER_{1993}. Aggregate regressions use data from both time periods.

The main variable of interest is return to education in the state-region, *ER*, the variable estimated from the wage equations of Tables 4 and 5. The first column uses OLS estimation and the second uses Instrumental Variables estimation. In the latter case, 1993 *ER* is used as an IV for 1999 *ER*; for it to be a valid IV, it must be correlated to the 1999 *ER* (which it is) and it must not be in the error term of the schooling equation in 1999. We argue that ER_{1993} is valid because it will not be correlated with shocks that occur after 1993 and which may affect both ER_{1999} and $EDYRS_{1999}$.

Schooling attainment (*EDYRS*) increases with age, as expected, up to age 17 years. Actual *EDYRS* as a proportion of possible *EDYRS* are expected to decrease with age, due to dropping-out of school at higher ages. Girls' educational attainment is 0.43 years less than that of boy rural children and 0.55 years less than urban children. The coefficient on the household per-capita expenditure variable (*pce*) implies that an increase in household per-capita expenditure from one standard deviation (SD) below mean *pce* to one SD above mean *pce* (i.e. by Rs. 716; see Table 3) increases *EDYRS* by 0.72 years. Schedule caste and schedule tribe children have 0.57 and 0.65 years less schooling than general caste children.

The individual-level relationship between *ER* and *EDYRS* is positive and significant, using the OLS estimator in column one. But how much does an increase in ER raise educational attainment? The size of the *ER* coefficient implies that if the return to education in the local labor market (*ER*) increases from one SD below the mean *ER* (see the last row of Table 3 for the mean and SD of *ER*) to one SD above the mean *ER* across state-regions, years of education acquired (*EDYRS*) increases by approximately 0.2 years – although as we will see in Table 8, the size of effect of *ER* on *EDYRS* is much greater for certain population groups than others. However, using the IV approach in column two, the relationship becomes smaller and is only significant at the 10% level, due to the larger standard error. The point estimates of the returns to education variable *ER* in the OLS and IV columns are not statistically significantly different, however. A Wald test shows that the null – that the coefficients on *ER* in the OLS and IV columns are equal – cannot be rejected at the 5% level.

4.2.2. Aggregate-level analysis

The individual educational attainment functions discussed above are not able to capture aggregate outcomes. Whilst we expect to find a positive relationship between *ER* and *EDYRS* at the individual level (at least in households that are not liquidity-constrained), at the aggregate level the relationship may be weaker or negative, owing to supply effects. One the one hand, high levels of educational attainment in a state-region may increase the supply of skilled labor into the regional labor market, leading to lower *ER*. On the other, high levels of educational attainment in a state-region may lead to economic growth and increased demand for skilled labor, raising *ER*. Either way, *EDYRS* and *ER* would be simultaneously determined though the net direction of bias is an empirical question.

The approach used to control for simultaneity bias is instrumental variables estimation. For a variable to be a valid IV, it must be highly correlated with the variable it instruments for, and must not be correlated with the error term of the equation of main interest. In the case of the variable ER_{1999}, its lagged value ER_{1993} fulfils both criteria: the variables are well correlated, and, by definition, ER_{1993} will not be correlated with time-variant effects that occur between the years,[9] although we cannot adequately control for time-invariant relationship between *ER* in 1999 and 1993. For that, we have used state-region fixed effects, exploiting the panel aspect of our data.

Data are aggregated separately for each year (1993 and 1999) at the state-region level. Variable values are the means for each state-region and each year. This yields:

$$\bar{e}_{jt} = \alpha + \beta \bar{X}_{jt} + \gamma er_{jt} + \delta t + \varepsilon_{jt}$$

where the average level of education in the *j*th region at time t ($\bar{e}_{jt}$) depends on a vector of averaged personal and demographic characteristics ($\bar{X}_{jt}$), the return to education in the region (er_{jt}), and a time dummy variable (*t*) to control for increases in schooling participation between the two years. In comparison with individual-level *EDYRS* estimation, the vector

Table 8. Individual education attainment functions: by household per capita expenditure (pce) quantile and gender.

Variable	All *pce* quantiles	0th–10th *pce* quantiles	10th–25th *pce* quantiles	25th–50th *pce* quantiles	50th–75th *pce* quantiles	75th–100th *pce* quantiles	Enrolment[a]
Female subsample							
ER	11.358***	15.319**	30.663***	19.756***	15.975***	1.798	38.008**
	(4.92)	(2.57)	(5.88)	(3.96)	(3.79)	(0.57)	(2.29)
HH-EXP	0.001***	−0.0001	0.006***	0.007***	0.003***	0.0002***	0.002
	(5.69)	(0.11)	(2.51)	(7.54)	(6.14)	(3.51)	(0.47)
HH-EDUC	0.175***	0.162***	0.145***	0.162***	0.159***	0.142***	
	(41.00)	(17.25)	(18.54)	(30.30)	(32.04)	(31.19)	
n	102556	11976	12866	25327	26004	26383	431
R^2	0.40	0.15	0.11	0.25	0.36	0.54	0.02
Mean *EDYRS*	4.225	2.142	2.672	3.422	4.480	6.021	
Male subsample							
ER	−3.875***	−16.930***	−6.139	3.163	7.140***	3.555*	13.784
	(2.64)	(3.69)	(1.45)	(1.14)	(3.09)	(1.82)	(0.96)
HH-EXP	0.001***	0.001	0.009***	0.004***	0.003***	0.0002***	0.001
	(9.12)	(0.95)	(3.98)	(4.43)	(6.94)	(4.52)	(0.23)
HH-EDUC	0.142***	0.128***	0.140***	0.136***	0.132***	0.122***	
	(47.93)	(14.22)	(19.31)	(28.15)	(31.19)	(30.94)	
n	115278	12222	13892	28279	29713	31172	457
R^2	0.47	0.23	0.29	0.35	0.45	0.60	0.03
Mean *EDYRS*	4.549	2.740	3.348	3.983	4.828	6.048	

Note: The dependent variable is *EDYRS* (years of education). Robust *t*-statistics in parentheses. *, **, and *** signify statistical significance at 10%, 5%, and 1% levels, respectively. Column headed '0th–10th' contains observations from households in the lowest decile of per-capita expenditure (*pce*), 10th–25th from *pce* quantiles 10–25, and so on. [a]Coefficients from an IV probit estimation of enrolment on a sample of children aged five and six years in households in the bottom decile of *pce* and where nobody has received any education. The value of R^2 in the Enrolment column is that of the pseudo-R^2 measure.

of variables used in estimation in columns three, four and five of table 7 was reduced, firstly to preserve degrees of freedom owing to the relatively low number of observations (only 77 per year), and secondly due to variables failing to add explanatory power to the estimation. Thus, the variables included in estimation are the state-region averages of age (*age*), education level of household heads (*hh*), household per-capita expenditure (*pce*), and of the dummy variable for urban location (*ur*), capturing the share of urban population in a state-region. In column five, estimation rests only on 1999 data and er_{1999} is treated as endogenous and instrumented with er_{1993}.

Columns three, four and five of Table 7 present OLS results at the state-region level. Column three presents OLS results, and the fixed-effects estimator in column four controls for state-region level unobserved factors, using the panel aspect of our data-set. The point estimate on the returns to education variable *ER* in the fixed effects results is very similar to the OLS estimate of column three. When we estimate the state-region-level educational attainment equations separately for males and females and for poor and non-poor samples (not reported), the point estimates of OLS and fixed effects estimators do not differ significantly either. Since the fixed effects estimator is a powerful control for the endogeneity of *ER* and its introduction does not alter the OLS coefficient on *ER*, we can reject the idea that unobserved heterogeneity across state-regions affects results.

The fact that the *ER–EDYRS* relationship turns negative (albeit statistically insignificant) in column three of table 7, compared with the individual-level results of columns one and two, suggests that *ER* and *EDYRS* are jointly determined and that higher *EDYRS* depress the local returns to education. The fact that a positive coefficient on *ER* is present in the individual-level estimations of columns one and two suggests that simultaneity *does* affect results at the aggregate level: it seems that a higher supply of educated workers in a region lowers the returns to education and that this negative supply-side feedback undermines our ability to detect any positive effect that returns to education may otherwise have on educational attainment. When this is addressed using an IV procedure, in the final column of Table 7, the *ER–EDYRS* relationship turns positive and is of approximately the same size as in the IV column of the individual-level results in Table 7.

In summary, the results show evidence of a small positive influence of returns to education on educational attainment at the individual level. At the aggregate level, these results are much weaker. This may be attributable to negative supply-side effects, or caused by low power of estimation due to the small number of observations at the aggregated level.

5. Effects of liquidity constraints on the *ER–EDYRS* relationship

To see the effects of liquidity constraints on the relationship between *ER* and *EDYRS*, we now present the schooling attainment equations separately for households at different points of the distribution of household per-capita expenditure *pce*. Households in the lower quantiles of the distribution of *pce* are likely to be more liquidity constrained than households higher up the distribution and, in the absence of a direct measure of liquidity constraint, we take the poor/non-poor distinction as proxying reasonably for the extent of liquidity-constraint of households.[10] In the Indian context, liquidity constraints may affect male and female schooling decisions differently. Thus, analysis of the effects of *ER* on *EDYRS* is presented for poor and non-poor households separately by gender. This yields more detailed insight into the role of liquidity constraints and gender bias in educational attainment.

We repeat the experiments presented in Table 7 for different quantiles of household per-capita expenditure (*pce*), and subdivided by gender.[11] Female educational attainment functions are based on female returns to education and male attainment functions on male returns, since female returns to education are more likely to be relevant for girls' schooling decisions, and male returns more relevant for boys' decisions. Detailed results are presented in Table 8.

The variable set used is identical to that in Table 7 but we do not present the coefficients of age, religion, caste and location dummies to save space. Estimation uses the IV approach.

Gender analysis yields three striking insights in Table 8: firstly, male schooling participation in the poorest households (the bottom 10 deciles) is dominated by the income effect predicted by the model in Section 2, as the negative significant coefficient on *ER* shows. To test the robustness of this result, a probit equation of enrolment was estimated for children who cannot be affected by the income effect: school enrolment of children of age five and six in households where no household member has received any education should only be affected by the substitution effect (since such young children are unlikely to do earned work). Neither the child nor any other household member will be subject to an income effect if *ER* increases. The large size of the sample allows the estimation of such an enrolment probit (Table 8). The coefficient of *ER* suggests that there is a positive association between returns to education and enrolment in this subgroup, thus reconfirming the hypothesis that in liquidity-constrained households, the effect of *ER* on male schooling participation is affected by the income effect. This result is also found in Gormly and Swinnerton (2003) and Edmonds (2004) for South Africa.

Secondly, for females of the same income group, the relationship is equally large, but positive in sign. This suggests that, in India, male children with some education have better possibilities of earning waged income than otherwise equivalent female children (i.e. the male opportunity cost of education is higher). For young females, this opportunity cost is smaller or absent, as their choices are more between domestic work and going to school. There is some support in the data for the notion that girls are less likely than boys to do market work in India: in the 5–20 age group, 7.5% of boys but only less than 3% of girls are in waged work.[12] Hence, for girls, the positive substitution effect of higher *ER* dominates any negative income effect and they exhibit a positive overall relationship between *EDYRS* and *ER*.

Thirdly, the data suggest that the monetary cost of education poses a barrier to education for both boys and girls in very poor households. For example, for girls the size of the *ER* coefficient increases significantly between the bottom decile and the 10th–25th quantiles. A Wald test on the null hypothesis H_0: $b_{ER\ 0\text{–}10} = b_{ER\ 10\text{–}25}$ is significant at the 6% level, suggesting that schooling participation responds to *ER* more in quantiles 10–25 than in the bottom decile. Thus, the data suggest that monetary costs do pose a barrier to female schooling participation in the poorest households. For males too, the relationship becomes positive at higher income groups, implying a stronger effect of the opportunity cost of education at low levels of household income.

It is noteworthy that, for the gender groups individually, the absolute effect of *ER* becomes sizable: in the female subsample 10th–25th percentile of *pce*, if *ER* increases from one SD below to one SD above mean *ER*, then *EDYRS* increases by one whole year. Given that mean *EDYRS* of girls in this *pce* group is 2.7 years (Table 8), a one-year increase in years of schooling is very substantial.

To summarize, the results in Table 8 show that, for the poorer parts of the population, returns to education play a more major part in educational decisions than for the richer part. Female educational decisions respond in the way theory predicts, with changes in the size of coefficients suggesting that the cash cost of education may act as a barrier to education for the females in the poorest households: female *EDYRS* responds less to labor market incentives in the bottom decile than in the 10th–25th quantile. Poor male children's educational decisions exhibit a negative relationship with *ER*, suggesting that boys have a higher opportunity cost of education, which plays out particularly in liquidity-constrained households. In areas where ER is higher, boys in poor households are withdrawn from school to take advantage of the higher return to their (existing) levels of schooling. In other words, the (negative) income effect of ER is greater for boys than for girls.

6. Conclusion

We find that the Mincerian return to education for adults in the local labor market influences schooling decisions of young people in India. The results pay attention to omitted variable and simultaneity biases, both at the individual and aggregate (state-region) levels.

At the individual level, we find strong relationships between monetary returns to education and schooling decisions. For girls, the relationship is positive and mostly highly statistically significant, although the cost of attending school still acts as a barrier to schooling for poor females. The data suggest that, for poor males, higher returns to education in the local labor market raise the opportunity cost of schooling, causing the relationship between educational returns and schooling participation to become negative.

These results suggest that schooling decisions are influenced not only by household income and taste for education, and by availability and quality of schools, but also by the prevailing economic returns to education in the local labor market. However, an increase in labor market returns to education could lead to unintended effects: poor males may acquire less education than otherwise, due to the negative income effect prevailing in a liquidity-constrained situation. Thus, in order for labor market incentives to work in the intended direction, they must be complemented by policies to alleviate liquidity constraints and to reduce opportunity costs of schooling for poor households, such as a policy of attendance-contingent cash subsidies.

The results here offer a preliminary insight into the role of economic returns in schooling decisions. Our understanding would benefit from further analysis of smaller geographical subunits than the state-region, allowing for alternative ‘labor market boundaries’ and from more explicit modeling and detection of liquidity constraints. This suggests promising avenues for future research in this area of economics of education.

Acknowledgements

The authors are grateful to Kenneth Swinnerton for helpful comments on the paper and to Måns Söderbom for helpful discussions on some of the issues in the paper. Any errors are the authors' own.

Notes

1. The model and notation used here stem from Gormly and Swinnerton (2003).
2. Note that discounting has been excluded for clarity.
3. The National Sample Survey (NSS) does not collect information on hours worked but rather records the number of half-days worked in the past week. We have ascribed four hours' work to each ‘half-day’ worked for two reasons. Firstly, because it seemed the most reasonable assumption for the sample of *waged* workers, which is the subsample we work with. While hours worked may be significantly longer for self-employed workers, among the sample of waged workers, the assumption of a eight-hour day seems reasonable (especially given the six-day week, rather than the five-day week prevalent in most developed countries). Secondly, we ascribed four hours to a ‘half-day’ because other studies using Indian NSS data have also assumed this (for example, Vasudeva-Dutta 2006).

4. The National Sample Survey Organization covers all 78 state-regions defined by it for the 55th round; however, one state-region the Jhelum Valley in Jammu & Kashmir is not covered in 1993 and hence is excluded from analysis in 1999.
5. Wage earners are those for whom a wage is recorded and whose activity status is recorded to be wage employment.
6. Measurement of the economic benefits of education has a long history, starting with Mincer's (1974) semi-logarithmic framework. A series of reviews by Psacharopoulos (1985, 1994), Psacharopoulos and Patrinos (2004), and Card (2001) document the large number of studies in the field. While accurate estimation is difficult due to ability bias, Mincerian returns are a widely used measure of the economic benefits of education and yield estimates not too different from those obtained from IV and twin studies (Card 2001).
7. See Kingdon (1998) and Kingdon and Unni (2001). While Duraisamy (2002) and Vasudeva-Dutta (2006) report returns to different *levels* of education for India, they do not report the marginal return to each extra year of education.
8. For example, a child dropping out of school to earn a wage will raise household expenditure, meaning the coefficient on *pce* could be downward biased; equally, unobserved family endowments may raise both *pce* and child schooling attainment, implying that the coefficient on pce could be upwardly biased.
9. ER_{1993} will not be correlated with shocks that occur after 1993 and that may affect both ER_{1999} and $EDYRS_{1999}$.
10. Income and wealth are widely used as proxies for the absence or presence of liquidity constraints (see, for example, Johnson, Parker, and Souleles 2006; Centeno and Novo 2007). Since consumption is smoothed income, it also serves as a proxy for the extent of liquidity constraints. This is reinforced by the fact that people with low incomes in India find it harder to borrow money due to a lack of assets/collateral.
11. We do not presume that our per-capita expenditure categories are exogenous. However, there is no clear way of addressing the potential endogeneity of *pce* category.
12. This is compatible with the existence of pro-male bias in education in India. Kingdon (2005) finds evidence of significant gender bias in household education expenditure allocations in India.

References

Angrist, J.D., and V. Lavy. 1999. Using Maimonides' rule to estimate the effect of class size on scholastic achievement. *Quarterly Journal of Economics* 114, no. 2: 533–75.

Attanasio, O., C. Meghir, and A. Santiago. 2005. Education choices in Mexico: Using a structural model and a randomized experiment to evaluate progresa. IFS Working Paper EWP05/01, Institute of Fiscal Studies, London.

Baland, J.-M., and J.A. Robinson. 2000. Is child labor inefficient? *Journal of Political Economy* 108, no. 4: 663–79.

Bhalotra, S. 2004. Parent altruism, cash transfers and child poverty. Bristol Economics Discussion Paper 04/562, Department of Economics, University of Bristol, UK.

Card, D. 2001. Estimating the return to schooling: Progress on some persistent econometric problems. *Econometrica* 69, no. 5: 1127–60.

Case, A., and A. Deaton. 1999. School inputs and educational outcomes in South Africa. *Quarterly Journal of Economics* 114, no. 3: 1047–84.

Centeno, M., and A. Novo. 2007. Identifying unemployment insurance income effects with a quasi natural experiment. Working Paper 10-2007, Estudos e Documentos de Trabalho, Bank of Portugal.

Drèze, J., and G.G. Kingdon. 2001. School participation in rural India. *Review of Development Economics* 5, no. 1: 1–24.

Duflo, E. 2001. Schooling and labor market consequences of school construction in Indonesia: Evidence from an unusual policy experiment. *American Economic Review* 91, no. 4: 795–813.

Duraisamy, P. 2002. Changes in the returns to education in India, 1983–94: By gender, age-cohort and location, *Economics of Education Review* 21, no. 6: 609–22.

Edmonds, E.V. 2004. Does illiquidity alter child labor and schooling decisions? Evidence from household responses to anticipated cash transfers in South Africa. NBER Working Paper 10265 National Bureau of Economic Research, Cambridge, MA.

Foster, A.D., and M.R. Rosenzweig. 1996. Technical change and human-capital returns and investments: Evidence from the green revolution. *American Economic Review* 86, no. 4: 931–53.
Freeman, R. 1975. Overinvestment in college training. *Journal of Human Resources* 10, no. 3: 287–311.
Gemmell, N. 1996. Evaluating the impacts of human capital stocks and accumulation on economic growth: Some new evidence. *Oxford Bulletin of Economics and Statistics* 58, no. 1: 9–28.
Gormly, S., and K.A. Swinnerton. 2003. *The effect of adult returns to schooling on children's school enrolment, theory and evidence from South Africa.* US Department of Labor, Washington D. C.
Gungor, A.D. 2001. The gender gap in Turkish education: A regional approach. *Middle-East Technical University Studies in Development* 28, no. 3–4: 339–60.
Hanushek, E. 2003. The failure of input based schooling policies. *Economic Journal* 113: F64–98.
Heckman, J.J. 1979. Sample selection bias as a specification error. *Econometrica* 47, no. 1: 153–61.
Johnson, D., J. Parker, and N. Souleles. 2006. Household expenditure and the income tax rebates of 2001. *American Economic Review* 96, no. 5: 1589–610.
Kingdon, G.G. 1998. Does the labour market explain lower female schooling in India? *Journal of Development Studies* 35, no. 1: 39–65.
———. 2005. Where has all the bias gone? Detecting gender bias in the household allocation of educational expenditure in India. *Economic Development and Cultural Change* 53, no. 2: 409–51.
Kingdon, G.G. and J. Unni. 2001. Education and women's labour Market outcomes in India, Education Economics 9, no. 2: 173–95.
Kremer, M., and D.L. Chen. 2002. Income distribution dynamics with endogenous fertility. *Journal of Economic Growth* 7, no. 3: 227–58.
Krueger, A.B. 1999. Experimental estimates of education production functions. *Quarterly Journal of Economics,* 114(2): 497–532.
Krueger, A.B., and M. Lindahl. 2001. Education for growth: Why and for whom? *Journal of Economic Literature* 39, no. 4: 1101–36.
Mincer, J. 1974. *Schooling experience and earnings.* New York: Columbia University Press.
Nelson, R.R., and E.S. Phelps. 1966. Investments in humans, technological diffusion and economic growth. *American Economic Review* 56, no. 1: 69–75.
NSS. 1993. Household Schedule 10.1, Quinquennial round on Employment and Unemployment, National Sample Survey, July 1993 to July 1994. National Sample Survey Organisation, Delhi.
———. 1999. Household Schedule 10.1, Quinquennial round on Employment and Unemployment, National Sample Survey, July 1999 to June 2000. National Sample Survey Organisation, Delhi.
Psacharopoulos, G. 1985. Returns to education: a further international update and implications. *Journal of Human Resources* 20, no. 4: 583–604.
———. 1994. Returns to investment in education: A global update. *World Development* 22, no. 9: 1325–343.
Psacharopoulos, G., and G. Patrinos. 2004. Returns to investment in education: A further update. *Education Economics* 12, no. 2: 111–34.
Schluter, C., and J. Wahba. 2004. Are poor parents altruistic? Evidence from Mexico. Working Paper, Southampton University, UK. http://www.wiwi.uni-frankfurt.de/profs/klump/D/koll/schluterpaper.pdf
Schultz, T.P. 1990. Testing the neoclassical model of family labor supply and fertility. *Journal of Human Resources* 25: 599–634.
———. 2004. School subsidies for the poor: Evaluating the Mexican Progresa poverty program. *Journal of Development Economics* 74, no. 1: 199–250.
Schultz, T.W. 1975. The value of the ability to deal with equilibria. *Journal of Economic Literature* 13, no. 1: 827–46.
Soumelis, C. 1981. Do rates of return matter for public and private educational decisions? *Higher Education* 10, no. 3: 353–61.
Tansel, A. 1994. Wage employment, earnings and returns to schooling for men and women in Turkey. *Economics of Education Review* 13, no. 4: 305–20.
———. 2002. Determinants of school attainment of boys and girls in turkey: Individual, household and community factors. *Economics of Education Review* 21, no. 5: 455–70.
Temple, J.R.W. 2001. Generalizations that aren't? Evidence on education and growth. *European Economic Review* 45, nos 4–6: 905–18.
Todd, P., and K. Wolpin. 2003. Using a social experiment to validate a dynamic behavioral model of child schooling and fertility: Assessing the impact of a school subsidy program in Mexico.

Working Paper # 03-022, Penn Institute for Economic Research. University of Pennsylvania, USA.

Vasudeva-Dutta, P. 2006. Returns to education: New evidence for India, 1983–1999. *Education Economics* 14, no. 4: 431–51.

Vermeersh, C. 2004. School meals, educational achievement, and school competition: evidence from a randomized evaluation. World Bank Policy Research Working Paper, no. 3523.

World Bank. 2003. *World development indicators.* Electronic source. World Bank Washington, D. C. Available at http://go.worldbank.org/U0FSM7AQ40.

Yamauchi-Kawana, F. 1997. Information, neighborhood effects and investment in human capital: Learning schooling returns in a dynamic context. Mimeo, University of Pennsylvania, USA.