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Private versus social returns to human capital: Education and economic growth in India

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ABSTRACT

This paper investigates whether differences between private and social returns to education of government sector employees can contribute to an explanation of the "micro–macro paradox" in the literature on education and growth. We hypothesize that in India educated people find privately rewarding jobs in a sector in which social returns are low, namely the government sector. This could help explain high returns to education at the micro level and small or negative coefficients on education growth in growth regressions at the macro level. The empirical results, which are consistent with this hypothesis, are based on an analysis of state-level data from India spanning 40 years.

1. Introduction

A common prior of economists and policy makers is that education is an important promoter of economic growth. Indeed, it has consistently been shown that the level of education has a positive association with subsequent economic growth (e.g. Barro, 1991; Benhabib and Spiegel, 1994). But there remains a considerable debate about the effect of education growth on economic growth (e.g. Benhabib and Spiegel, 1994; Krueger and Lindahl, 2001; Pritchett, 2001; Temple, 2001; Pritchett, 2006). These findings generate a "micro–macro paradox" (Pritchett, 2001) in the empirical literature: studies at the micro level find throughout that more education is economically beneficial for an average individual (e.g. Psacharopoulos, 1994) and educated individuals also receive, on average, other private benefits, for example with respect to health, while at the macro level this is less clear, with some studies even finding negative effects of education growth on economic growth. A potential explanation for the micro–macro puzzle is that private and social returns to education differ. This might in particular be due to the role that the government sector plays as an important employer of educated people in many countries (e.g. Murphy et al., 1991; Pritchett, 2001).

Our goal in this paper is to contribute to this literature in several ways: First, we provide an in-depth study of the importance of this micro–macro puzzle for a large country in which it is particularly striking, namely India. We will study the time period 1961–2001, a period with, on average, a significant expansion of education. Second, we hypothesize and test via cross-state regressions a specific mechanism that may explain a divergence of micro and macro findings: The hypothesis is that educated people find privately rewarding jobs in a sector in which social returns are low relative to the private

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returns, namely the government sector. Third, because we use within-country variation for our empirical work we keep many important aspects of the economic and social environment constant and thus can be more confident than with cross-country work that unobserved differences across units of observation or parameter heterogeneity are not driving the results. Fourth, by using variation across Indian states and measures of educational attainment from the regularly conducted censuses, we can provide estimates that are not afflicted by the data comparability and data quality problems that typically exist in cross-country work and that may explain some of the existing findings of small growth effects (see Krueger and Lindahl, 2001; Cohen and Soto, 2007; de la Fuente and Doménech, 2006).

Social returns in the government sector may be low for at least two reasons, namely (a) through direct effects, because government sector employees work in unproductive positions, or (b) through indirect effects, because government sector employees exert negative externalities on the productivity of the private sector, e.g. through government regulations, licensing requirements, or individual rent-seeking activities. Particularly if these reasons are more likely to be relevant in countries with high educational growth and large government sectors, like India, this could explain why educational growth does not consistently show a significantly positive relationship with economic growth in cross-country regressions.

Indeed, in many developing countries the government sector is large, particularly as an employer for the educated. Gelb et al. (1991) provide a theoretical explanation that is consistent with theories of rent-seeking behavior, in which governments hire in response to unemployment, which leads to surplus labor in the government sector. Jaimovich and Rud (2012) provide a model in which bureaucrats' rent-seeking behavior leads to an equilibrium with low aggregate output and low levels of entrepreneurship. At the same time there is significant anecdotal evidence for the importance of rent-seeking in these large government sectors, which implies both the direct and indirect reasons for low productivity in the public sector suggested above. For example, Murphy et al. (1991) note that in "many African countries in this century, government service, with the attendant ability to solicit bribes and dispose of tax revenue for the benefit of one's friends and family, was the principal career for the ablest people in the society" (Murphy et al., 1991, p. 505). Pritchett (2001, p. 384) cites the case of Egypt where government guarantees of employment led to a government sector that, in 1998, employed seventy percent of university graduates. Gelb et al. (1991) put together data for 14 developing countries to show that government employment not only constitutes a significant share of all non-agricultural employment in these countries but that it was also growing more rapidly than wage-employment in the private sector over the 1960s and 1970s.

Regarding India, Banerjee (2006, p. 1021) states that "[…] highly qualified engineers, educated at great public expense […] cooled their heels as minor functionaries in the overfilled bureaucracies of large public companies". In the appendix we provide additional evidence at the micro level that supports the above-mentioned anecdotal evidence and that suggests a specific mechanism that leads to our findings at the macro level: India's public sector paid substantially above private sector wages and, presumably in part because of this public-sector wage premium, attracted many of India's well-educated individuals.[1] In addition, it is often argued that India's bureaucracy created a mass of regulations whose effect was to inhibit India's economic growth. In sum, the attributes of India's public sector have allowed a critical mass of workers in that sector to be the well paid, but relatively unproductive, professionals that are at the core of the hypothesis of this paper.

India presents a paradigmatic case of the effect that is described in some of the empirical papers cited above: a country with substantial educational growth (despite still low absolute levels of education) yet relatively paltry economic growth, in the period before the reforms of the 1980s and early 1990s. We estimate, based on data from Barro and Lee (1993), that the worldwide average of the annual growth rate of average years of schooling (as a proxy for educational capital), was 2.6 percent between 1960 and 1985. India's growth rate of the population's average years of schooling during this period was 3.4 percent. Over the whole period, this suggests that India's educational capital increased by a factor of 2.3; whereas, worldwide educational capital increased by a factor of 1.9. At the same time, India's annual average growth rate of per capita real GDP over this period was just over 1.8 percent, compared to a world average of 2.3 percent. Thus, India was an underperformer in economic growth despite its relatively impressive educational capital growth.

The paper is not trying to argue against government generally. Indeed, a certain number of government employees is required to provide a sufficient institutional framework; the government also provides other important services and public goods. In a transition process, it might also be beneficial to have a significant number of government employees working in state-owned enterprises. However, we hypothesize that in the particular case studied, a share of India's government sector employment led to a wasteful diversion of human capital and that India's bureaucracy undermined the potential of India's education growth to contribute to economic growth because of its particular attributes. The suggestion that India's bureaucracy has had limited success in promoting economic growth in the time period that we study is neither unique nor particularly controversial. Especially the role of its complicated set of regulations is studied extensively in the literature (e.g. Aghion et al., 2005, 2008; Besley and Burgess, 2004; Sivadasan, 2003). Previous research has also shown that the long-run level of income in Indian states is positively affected by levels of education (Trivedi, 2006). What is new is the connection that we suggest and test between the bureaucracy and the role of education as a promoter of economic growth.

[1] The workings of the labor market and the methods of promotion in the public sector also suggest that productivity was not commensurate with wages. Blaug et al. (1969) suggest the existence of a queue system, where public sector jobs, for which the supply was too large because the wage was set above market levels, were – at least to some extent – allocated by waiting times. Further, employment was often secured not by added qualifications or even time but rather by means of personal contacts. Indeed, this was the most often cited means of securing a job in a study of graduates of Delhi University in 1960 (Blaug et al., 1969).

Our hypothesis has the following testable implications: first, that educational expansion was effective in promoting growth in the absence of the effect of bureaucracy, and second, that the larger the bureaucracy in a given Indian state, the less effective educational expansion was in promoting growth. The findings of our cross-state regression, in which we also take into account concerns about the endogeneity of key regressors, are in line with the hypothesis: After accounting for the role of government we find that state-level economic growth is positively related to education growth in states with small governments. On the other hand, the baseline regressions, those without controlling for government sector effects, resemble the findings of the cross-country literature (e.g. Benhabib and Spiegel, 1994; Pritchett, 2001): state-level educational expansion has no statistically significant association with state-level economic growth.[2]

The paper proceeds as follows. We first discuss the importance of government employment in India. We then provide some theoretical considerations to guide the econometric analysis. Next, we test the predictions of this theoretical framework with cross-state regressions using a variety of methods and robustness checks. After a consideration of possible alternative explanations we conclude.

2. Background on public sector employment and education in India

The paper's main hypothesis is based on the argument that the public sector attracted a large fraction of educated individuals over the study period. Before moving to the econometric analysis, we therefore provide systematic evidence on (a) the size of the public sector employment in the Indian economy and (b) the large fraction of educated individuals that worked in the public sector.[3]

The size of public sector employment in the Indian economy: For the suggested mechanism to be meaningful at the macro-level, the Indian government sector needs to have a significant size relative to the rest of the economy. On average, in states that enter the core sample, 5.3% of the individuals that are between 15 and 59 years old are employed by the government sector (see Table C1 with the summary statistics in the appendix). While this might seem low at first, one should consider the size of the organized sector and its importance for GDP.

In India, most of the official data on employment refer to employment in what is termed the “organized sector”. This is employment in the public sector or in registered private firms above a certain size (for data referring to 1961 the cut-off is twenty-five workers (Blaug et al., 1969); for data referring to years after 1971 the cut-off is 10 workers). For 1977, the earliest year for which we could obtain these data on a consistent basis, the total organized sector employment was 20.6 million people. In later years, reported numbers are 26.7 million (1991) and 27.8 million (2001) people. The Economic Surveys of India provide estimates of total employment, which are based on survey data from the NSS (National Sample Survey): According to those estimates total employment, for example, in 1983 was 302 million people. Thus less than 10 percent of the employed work in the organized sector. Relative to the size of the organized sector, the number of public-sector employees is large: In 1977, out of 20.6 million people working in the organized sector, 13.8 million, i.e. 67%, were employed in the public sector. In 1981, this number was 68% (Economic Survey of India 1992–1993). In 1991, this share increased slightly to 71% and in 2001, the share was 69%.

While the employment share of the organized sector is relatively small, the organized sector's contribution to GDP is disproportionately large. Again, data on this are difficult to come by, but Raveendran (2006), for example, estimates (based on NSS 2004/2005 data) that the organized sector contributes about 41% to India's GDP.

The bottom line is that (throughout the period studied in this paper) although only about 5% of working-age Indians work for the public sector, the public-sector employees constitute the majority of all organized-sector employment. In addition, putting the various estimates together suggests that in 2004/2005 the public sector was responsible for roughly 25% of India's GDP.[4]

The share of educated individuals working in the public sector: The discussion of the size of the public sector employment in the Indian economy above shows the importance of the government sector relative to the total organized sector. However, one might still be unconvinced that the size of the government sector relative to total employment is meaningful enough to be able to perform the role that is hypothesized, namely that it employs a significant share of the *educated* individuals. This subsection therefore brings together evidence to support this assertion.

The first piece of systematic evidence is based on census data: Although the demographic census data do not in general allow us to distinguish between individuals employed in the private sector and those employed in the public sector, one exception is the 1971 census, which published a specific volume on “degree holders and technical personnel” (India, Office of the Registrar General, 1975). This publication summarizes some information about the approximately 1.3 million degree

[2] Our findings are also in line with findings by Rogers (2008) in a cross-country framework. Rogers (2008) finds that countries with lower levels of corruption and those with a lower black-market premium, which are assumed to use schooling productively, show a stronger association between schooling and economic growth.

[3] The purpose of this section is simply to establish the importance of the public sector for educated individuals. Among the likely reasons for this are a large public-sector wage premium and higher job security in the public sector. The data suggest that public–private sector wage differentials were substantial and increased over the studied period. Bardhan (1984) summarizes the changes in wages of public sector workers, noting, “the salary demands on the budget, largely from white-collar workers, [grew] staggeringly” between 1950 and 1980 (Bardhan, 1984, p. 62). Bardhan notes that during the 1960s and 1970s, real wages of public sector employees grew at a rate that was more than twice the growth of overall wages. These indirect indications can be supplemented with direct evidence of public–private wage differentials from the end of the period under study, which we provide in Appendix A.

[4] The public sector constitutes about two-thirds of the official sector, which in turn is estimated to account for 40% of GDP: $0.4 \times 0.66 = 0.264$.

Table 1
Share of individuals with the highest levels of education in the public sector.

State	Share of degree holders working in the public sector			Share of individuals with education of secondary and above working in the public sector	
	1971	1993	1999/2000	1993	1999/2000
India	0.64	0.63	0.54	0.61	0.51
Andaman and Nicobar Islands	0.94	0.91	0.84	0.87	0.82
Andhra Pradesh	0.75	0.65	0.50	0.60	0.45
Arunachal Pradesh	0.97	0.72	0.71	0.75	0.72
Assam	0.68	0.79	0.74	0.80	0.70
Bihar	0.62	0.66	0.49	0.66	0.47
Chandigarh	0.85	0.74	0.69	0.59	0.56
Dadra and Nagar Haveli		0.50	0.14	0.54	0.14
Delhi		0.68	0.55	0.60	0.44
Goa		0.51	0.40	0.53	0.37
Gujarat	0.52	0.52	0.42	0.45	0.43
Haryana	0.72	0.59	0.50	0.56	0.45
Himachal Pradesh	0.90	0.83	0.78	0.84	0.73
Jammu and Kashmir	0.93	0.84	0.76	0.82	0.73
Karnataka	0.64	0.59	0.47	0.56	0.45
Kerala	0.58	0.64	0.55	0.61	0.47
Lakshadweep		0.70	0.96	0.97	0.92
Madhya Pradesh	0.81	0.33	0.59	0.68	0.57
Maharashtra	0.48	0.89	0.40	0.32	0.37
Manipur	0.73	0.91	0.70	0.87	0.69
Meghalaya	0.79	0.94	0.88	0.84	0.83
Mizoram		0.91	0.79	0.94	0.76
Nagaland	0.85	0.66	0.82	0.91	0.88
Orissa	0.77	0.71	0.68	0.69	0.68
Pondicherry		0.69	0.48	0.63	0.44
Punjab	0.69	0.77	0.57	0.62	0.48
Rajasthan	0.80	0.88	0.66	0.70	0.61
Sikkim		0.59	0.89	0.87	0.92
Tamil Nadu	0.60	0.89	0.41	0.54	0.36
Tripura	0.87	0.63	0.47	0.85	0.46
Uttar Pradesh	0.59	0.50	0.53	0.62	0.48
West Bengal	0.54	0.49	0.45	0.53	0.46
Correlation with current government sector size (government employees/working age population)	0.45	0.39	0.40	0.29	0.32
p-Value	0.047	0.052	0.038	0.155	0.101

Notes: 1971 data are calculated from census publications; 1993 and 1998 data are calculated based on NSS sample data (Rounds 50 and 55) using only individuals whose primary status is "wage earner"; for correlations with NSS data from 1993 and 1999/2000 government sector sizes from 1991 and 2001, respectively, are used.

holders in 1971, i.e. mostly individuals with a Bachelor or a Master degree.[5] These individuals constitute approximately 4% of the 32.6 million Indians in 1971 that had at least a matriculation degree. For these most highly educated individuals we find that 64% work in the public sector (see the first column of Table 1). Even in the state with the smallest share of educated individuals working in the public sector (Maharashtra), still 48% of degree holders work for the public sector.[6]

Secondly, we use household survey data from the National Sample Survey (NSS) micro data. Every five years the National Sample Survey Organization uses an additional questionnaire (schedule 10) with detailed information on employment. NSS data from 1993 (round 50) and 1999/2000 (round 55) allow us to identify whether individuals work for a public or a private employer. Note that results of the 1993 and 1999 NSS rounds are not fully comparable because of differences in the NSS questionnaire.[7] We restrict the NSS sample to those individuals working for a wage for which the public/private distinction

[5] Out of a total of 1,294,133 employed individuals with degrees, approximately 838,000 have a Bachelor or equivalent degree, 300,000 have a Masters or "Post Graduate" degree, 121,000 have a "Diploma", 20,000 have a "Certificate" and 14,000 hold a "Doctorate".

[6] Data reported in Blaug et al. (1969) confirm these findings for the beginning of the study period. In 1961 two-thirds of workers with graduate degrees and almost as many workers with secondary educations worked in the public sector (Blaug et al., 1969).

[7] For 1993 there is a direct question about public/private sector (namely about the "nature of employer", which has the three options: public/semipublic/private, and is answered by almost all individuals whose "principal status" is "worked as regular salaried wage employee"); in 1999 it is more difficult to distinguish public versus private sector employees: the question is mainly referring to enterprises (in 1999/2000, the question is about the "enterprise type", with 8 answer categories). The focus of the analysis is therefore on 1993 data. The samples are restricted to those individuals whose "principal status" is "worked as regular salaried wage employee" and who report a wage (cash or in-kind).

can be made. Columns 2–5 of Table 1 show the results. Overall, the share of degree holders and those with at least a secondary education in the public sector remains high in the 1990s. These shares are estimated to be between 51 and 63%. In most states, more than half of the most educated individuals work in the public sector. The last two rows of the table show that the share of the most highly educated (graduate degree holders) working for the government is strongly correlated with government sector size. For individuals with at least a secondary education the correlation coefficient and the statistical significance of the positive correlation are somewhat smaller (with p-values around 0.1 and 0.15).[8]

In sum, the above discussion confirms that (a) the public sector attracted the majority of individuals with higher levels of education and (b) the public sector constituted the majority of all employment in the organized sector. In light of these numbers the hypothesis spelled out in the introduction seems plausible. The purpose of the remainder of this paper is to test this hypothesis econometrically.

3. Empirical specification and estimation

3.1. Hypotheses and empirical specifications

Several approaches have been used to model the contribution of human capital in the form of schooling to economic growth. It is the role of education *growth*, as opposed to the level of education, that continues to be debated in the literature, thus our focus is on the specifications that include this variable. The prediction that growth of human capital in the form of schooling creates growth in per capita GDP can be derived from endogenous growth theories in the spirit of Lucas (1988) that add human capital to the aggregate production function framework and assume constant returns to scale to the reproducible factors. An alternative approach is to start from the standard (micro-)Mincer equation, which relates the log of wages to years of schooling, and aggregate up to a "macro-Mincer" equation (Heckman and Klenow, 1997; Krueger and Lindahl, 2001; Mincer, 1974). There is an argument as to whether the key human capital regressor in the empirical specification should be the logarithm of average schooling in the population, i.e. a log–log specification, or whether the regressor should be the level of average schooling (Topel, 1999; Krueger and Lindahl, 2001).[9] In our empirical work we will focus on the more common log–log specification of human capital, in which the human capital regressor is log(S), where S is the average years of schooling.

In an influential early paper, Benhabib and Spiegel (1994) find that, controlling for growth of population and physical capital accumulation, human capital accumulation is not significantly associated with economic growth in all specifications and negative in all but one of their twelve specifications. Pritchett (2001) similarly finds no significant correlation between increases in educational capital and GDP growth per worker.[10] Commenting on these results, Krueger and Lindahl (2001) and de la Fuente and Doménech (2006) argue that data quality can explain many of the empirical results in the literature. Further, Krueger and Lindahl (2001) argue that including the change in physical capital as a control could bias the results downward if, because of complementarities, educational growth increases economic growth in part by attracting physical capital. In their panel analysis they leave out the growth of physical capital. Using a linear specification of the human capital measure (i.e. where the human capital regressor is S, the average years of schooling) they find a significant association of education growth with GDP growth over long periods (of at least ten years). Temple (1999), using the data by Benhabib and Spiegel (1994), shows that using the Least Trimmed Squares estimator results in a significant coefficient on schooling growth. For the specific case of India, Trivedi (2006) studies the relationship between levels of education and levels of income using state-level data. Employing the Pooled Mean Group estimator, Trivedi (2006) finds that the stock of education has a positive impact on the steady-state level of per capita state domestic product.

3.2. Introducing the role of government

In the standard models that model the effect of education growth on economic growth, the underlying assumption is that educated individuals undertake productive activities. However, Murphy et al.'s (1991) model demonstrates that where rent seeking is rewarded more highly than productivity, this assumption breaks down. Instead, workers may use their education to gain access to rent-seeking opportunities, with the result that educational growth has little or no effect on economic growth. Because these educated workers are earning high wages, the microeconomic relationship between educational level and wages remains.

To arrive at an estimating equation, we model the role of education growth in the presence of rent-seeking in the government sector by adjusting an aggregate Cobb–Douglas production function to take into account the possibility of unproductive human capital.[11] Consider an aggregate Cobb–Douglas production function with the inputs physical capital

[8] It should be noted that the government sector does not exclusively hire relatively highly educated individuals. For example, in the 1993 NSS data about 29% of individuals who work in the public sector have a "middle" level of education or less and 16% have a primary school education or less.

[9] In the case of the macro-Mincer specification, the derivation from the micro-level wage equation immediately implies that the level of average schooling and not its log is the appropriate specification, while the appropriate specification of human capital is less clear in the other estimating equations.

[10] Studies that focus on literacy expansion also show no effect on GDP growth (e.g. Behrman, 1987).

[11] We would end up with a similar estimating equation if we followed the macro-Mincer wage equation approach that was referred to in the previous section. For expositional purposes the focus here is on one approach.

(K), labor (L), and human capital (H):

$$Y_t = (K_t)^{\alpha}(H_t)^{\beta}(L_t)^{\gamma}A_t$$

Assuming constant returns to scale[12] we can rewrite this in per capita terms,

$$\frac{Y_t}{L_t} = \left(\frac{K_t}{L_t}\right)^{\alpha}\left(\frac{H_t}{L_t}\right)^{\beta}A_t$$

Now, assume that the economy's total existing human capital H can be of two types: Human capital that is being used productively, H^p, and human capital that is idle, H^{idle}, such that $H = H^{idle} + H^p$. Only the productive human capital, H^p, enters the aggregate production function:

$$\frac{Y_t}{L_t} = \left(\frac{K_t}{L_t}\right)^{\alpha}\left(\frac{H_t^p}{L_t}\right)^{\beta}A_t$$

Taking logs and differencing, and using lower case letters to denote variables in per capita terms, we get

$$\Delta\log(y_t) = \alpha\Delta\log(k_t) + \beta\Delta\log(h_t^p) + \Delta\log(A_t)$$

Without the assumption that only a part of the total human capital enters the production function, this equation could be taken to the data as is done in similar form in a number of papers, including Benhabib and Spiegel (1994), Krueger and Lindahl (2001) and Pritchett (2001). In our case, however, we first need to be more specific about how the productive part of human capital is determined as opposed to the idle part. Our main hypothesis for the case of India is that a large (state) government absorbs some share of the flow of newly educated individuals without employing them in a productive activity. We further hypothesize the possibility of destructive activities via negative externalities. Additionally, we need to consider that – although the majority of the relatively highly educated individuals (i.e. those with at least a secondary education) work for the government – a significant number of individuals in the public sector has lower levels of education (primary and middle). Also a large part of the increase in the average years of schooling over the sample period occurred at the middle and lower end of the distribution. For all these reasons we need an empirical specification that does not restrict the government sector's effect to either the highly skilled or the individuals employed in the government sector.

Further, it seems plausible that there are limits to the percentage increase in unproductive individuals that the government can hire.[13] Thus, a public sector that is initially large, can absorb more unemployed individuals in absolute terms. Consequently, growth of human capital (in the form of schooling growth) translates into lower growth of productive human capital (capital that is not diverted by government) if the beginning-of-period government sector is larger. This, in turn, directly suggests to model the growth of productive human capital as a function that includes an interaction term between government sector size (gov) and human capital growth. The specific functional form that we assume for the empirical work is as follows:

$$\Delta\log(h_t^p) = \zeta\Delta\log(h_t) + \gamma gov_{t-1}\Delta\log(h_t) \tag{1}$$

where we hypothesize that γ is negative (and $\zeta \leq 1$). Note that this specification not only allows for direct absorption of educated individuals in unproductive (state) government jobs, but also includes the possibility of a loss of productive human capital at any level of education due to negative externalities of large governments.

This formulation then allows us to use a standard measure of human capital in empirical work, as it implies:

$$\Delta\log(y_t) = \alpha\Delta\log(k_t) + \beta[\zeta\Delta\log(h_t) + \gamma gov_{t-1}\Delta\log(h_t)] + \Delta\log(A_t)$$

or, defining $\tilde{\zeta} = \beta * \zeta$ and $\tilde{\gamma} = \beta * \gamma$:

$$\Delta\log(y_t) = \alpha\Delta\log(k_t) + \tilde{\zeta}\Delta\log(h_t) + \tilde{\gamma} gov_{t-1}\Delta\log(h_t) + \Delta\log(A_t) \tag{2}$$

The main hypotheses that we are going to test are that $\tilde{\gamma}$ is negative and that $\tilde{\zeta}$ is positive.

3.3. Estimation

Eq. (2) is the basis of the specification that we take to the data. To disentangle the interaction effect $\tilde{\gamma} gov_{t-1}\Delta\log(h_t)$ and the pure effect of government size, we also include gov_{t-1}. Further, we add the beginning-of-period level of (log-) income,

[12] This approach allows for a direct comparison of the present empirical work with standard growth regressions that have *levels* of human capital as the main right-hand side variable. Alternatively, if one was not willing to assume constant returns to scale, one could follow closely Benhabib and Spiegel (1994), who in their baseline regressions use absolute values instead of per capita terms (here omitting the error/productivity term):

$$\Delta\log(Y_t) = \alpha\Delta\log(K_t) + \beta\Delta\log(H_t) + \gamma\Delta\log(L_t)$$

and proceed from here as is being done in the text under the assumption of constant returns to scale.

[13] Gelb et al. (1991), for example, list 14 developing countries, in which public sector employment increases on average by 5.5% over the 1960s and 1970s, the maximum being 8% annually (according to these numbers private sector employment increases on average by 0.3%).

log (y_{t-1}), as is a commonly done in this literature (e.g. Benhabib and Spiegel, 1994).[14] After adding subscripts i, to indicate that we work with a panel of states, time fixed effects μ_t, and adding an error term, the baseline empirical specification therefore is

$$\Delta\log(y_{it}) = \alpha\Delta\log(k_{it}) + \tilde{\zeta}\Delta\log(h_{it}) + \tilde{\gamma}gov_{it-1}\Delta\log(h_{it}) + \delta gov_{t-1} + \theta\log(y_{it-1}) + \mu_t + \varepsilon_{it} \tag{3}$$

In our main specifications, we investigate 10-year interval and use annualized growth rates. We also include state fixed effects in most regressions to control for state specific effects. We also note that using the within-country/cross-states analysis keeps many other usually unobserved variables constant, reducing the omitted variable problem of cross-country regressions.

Despite the ability to control for state and time fixed effects and the comparability of data across states and time, there will remain lingering doubts about endogeneity, and it is important to consider first in how far in India endogeneity might indeed be a problem. In this context, it is useful to consider the reasons for the rapid expansion of schooling in India. India's nationalists came to power in 1947 promising a complete revolution from the British colonial regime.[15] Where the British had restricted education to an elite, the new Indian constitution promised universal, compulsory primary schooling. Specifically, the intention was to achieve universal free education for all children under fourteen within ten years of independence. This was enshrined as a Directive Principle of the Indian Constitution (Constitution of India, Article 45). While this grand goal was not achieved in that time period – and, indeed, remains unfulfilled today – the Indian government nonetheless made substantial progress. For example, the percentage of children aged 6–11 enrolled in grades I–V rose from 42.6% in 1951 to 62.4% in 1960 (Panchamukhi, 1996, p. 128).

Thus, for the leaders of India's young republic, as for many post-colonial leaders, educational expansion was a centerpiece of both social and economic policy, and education growth was to a large extent driven by exogenous political events. Variations in education expansion across states in turn are then plausibly driven to some extent by historical differences in education policies and exogenous differences in initial conditions, including the number of educated individuals who could serve as teachers. Regarding the possible endogeneity of government sector size we note that, due to the legal environment, adjustment, i.e. hiring and firing, in the government sector is difficult and there is likely considerable inertia in the size of the government sector that makes endogenous determination less likely than in countries with a less protected civil service.[16]

Despite the above argument about the variation in education growth (and government sector size) that is due to historical conditions or the legal environment, the plausible endogeneity of these variables requires our attention. To deal with this we exploit the panel structure of the data and use a dynamic panel estimator (Arellano and Bond, 1991; Blundell and Bond, 1998), in addition to using fixed effects, pooled OLS and seemingly unrelated regressions estimators. The use of the Arellano and Bond (1991) estimator is advocated for cross-country regressions, for example, by Caselli et al. (1996); advantages of the Blundell and Bond (1998) over the Arellano and Bond (1991) approach in the context of growth regressions are discussed in Bond et al. (2001).

For some specifications we require physical capital data. Unfortunately, state-level physical capital data are unavailable for Indian states (see, e.g. Economic and Political Weekly Research Foundation, 2003, 2004; Trivedi, 2006). To partly deal with the problem that capital stock data do not exist at the state level, we use data on electricity E (in kwh per capita) as an additional control in our regressions. Arguably, electricity use and capital stock are highly correlated. Further, we were able to collect information on two important subcategories of physical capital. In robustness checks in Section 4.3 we will use these additional sources of data. The first is a measure of physical capital employed in manufacturing, which comes from the EPW Annual Survey of Industries (ASI) database (Economic and Political Weekly Research Foundation, 2002). Second, we use data on the number of tractors in a state; further details will be given below. We also note that Krueger and Lindahl (2001), who also lack capital stock data for their regressions that use 5 or 10 year intervals, argue that omitting capital may be justified if physical capital growth and educational capital growth are correlated because educational capital growth attracts physical capital.

3.4. Cross-state data

The main data used for the analysis come from the Indian census in the years 1961, 1971, 1981, 1991, and 2001. For each of these years, data that are comparable across states and over time are available regarding the educational level of India's residents, and thus we can largely rule out data comparability problems as an explanation for the findings of small growth effects (see Krueger and Lindahl, 2001; de la Fuente and Doménech, 2006). From these data we derive our measure of

[14] Benhabib and Spiegel (1994) note that the interpretation of initial income in a specification that is derived from an aggregate production function is unclear. They argue that “initial income may proxy for initial technological advantage and […] the negative coefficient may be interpreted as a ‘catch-up’ result” (p. 151). Another possible interpretation is that the lagged dependent variable helps to proxy for serially correlated omitted variables (we thank a referee for pointing this out).

[15] A comprehensive analysis of the history of education in India can be found, for example, in Blaug et al. (1969), Pandey (1992), Panchamukhi (1996) or Mukhopadhyay and Parhar (1999).

[16] In a previous version of this paper, an analysis was also performed at the industry level, exploiting variation across industries within a state to deal with endogeneity concerns. This analysis of industrial growth gives similar results and it is even more difficult to think of mechanisms that would suggest endogeneity driving the results across different industries. The earlier version of this paper is available upon request.

Table 2
State-level summary statistics for annual growth of average years of schooling of the working age population (15–59 years old).

Time period	Observations	Mean	Standard deviation
1961–2001	25	0.050	0.017
1961–1971	17	0.105	0.040
1971–1981	19	0.023	0.015
1981–1991	23	0.030	0.012
1991–2001	25	0.018	0.010

Note: Decade values (rows 2–5) restricted to core sample.

Table 3
Education growth and SDP growth by decade: baseline results.

	(1) Pooled	(2) Pooled	(3) FE	(4) FE	(5) SUR	(6) SUR
$\Delta\log(S)$	0.084	0.065	0.090	0.083	0.069	0.008
	(1.30)	(0.90)	(1.33)	(0.90)	(0.96)	(0.10)
$\log(\mathrm{SDP}_{t-1})$	−0.002	0.001	−0.099	−0.105	0.005	0.008
	(0.26)	(0.16)	(5.75)***	(5.09)***	(0.65)	(1.07)
$\Delta\log(E)$		0.081		0.048		0.107
		(1.71)*		(0.78)		(2.22)**
1970s	0.007	0.011	0.019	0.022	0.006	0.007
	(1.14)	(1.54)	(3.08)***	(3.32)***	(0.79)	(0.83)
1980s	0.013	0.013	0.035	0.036	0.011	0.009
	(2.08)**	(2.36)**	(5.19)***	(5.12)***	(1.63)	(1.46)
1990s	0.035	0.038	0.076	0.081	0.031	0.032
	(4.53)***	(4.98)***	(6.67)***	(6.21)***	(3.93)***	(4.35)***
Observations	92	86	92	86	92	86
R-squared; in (3) and (4) the within R-squared is reported	0.30	0.35	0.61	0.63		

Note: Heteroskedasticity-robust *t*-statistics are in parentheses.
*** Indicates significance at 1%.
** Indicates significance at 5%.
* Indicates significance at 10%.

human capital growth, the annualized change in $\log(S)$.[17] All per-capita measures are relative to the working-age population (but we have confirmed that the main results are robust to using the total population). Table 2 presents summary statistics for changes of the state-level human capital measures used for the core sample.

The primary dependent variable in our analysis is net real per capita state domestic product (SDP). Per capita SDP data come from Özler et al. (1996) and India's Ministry of Statistics and Programme Implementation (see Ministry of Statistics and Programme Implementation, no year a, b, online resource) and are corrected for inflation (the details are in Appendix B). We also have separate data for the contribution of the public administration to SDP, which allows us to exclude the public administration's contribution from the SDP growth calculations in robustness checks.

Population figures are from census data and data on government employment come from the Statistical Abstracts published by India's Central Statistical Organization. The proxy for government sector size (gov) is government employment as a percentage of the working age, i.e. 15–59 years, population (details are in Appendix B). Not all variables exist for all state-year observations. However, the missing states and territories are mostly small, and for the key results we end up with a sample of states that covers in 2001, for example, 93.3% of the total Indian population. The appendix (Table C1) provides summary statistics for state/decade observations of the key variables employed in the regression analysis.

4. Results from cross-state regressions

4.1. Baseline results

We start with the standard framework, i.e. without consideration of variables related to government sector size, and first show results from various specifications that do not yet take the possible endogeneity of some of the variables into account. To make the econometric approach comparable to Krueger and Lindahl (2001) we first show results that use pooled data, in which we correct for correlation of the standard errors within a state (see Table 3, columns 1 and 2). For the results in

[17] We further discuss the question whether the years of education variable is a good proxy for quality of education (or human capital more generally) below.

Table 4
Education growth, government sector size, and SDP growth.

	(1) FE	(2) FE	(3) FE	(4) FE	(5) pooled	(6) pooled	(7) SUR	(8) SUR
$\Delta\log(S)$	0.083	0.077	0.223	0.206	0.167	0.172	0.150	0.140
	(1.24)	(1.18)	(2.73)**	(1.79)*	(1.80)*	(2.18)**	(2.13)**	(2.65)***
gov_{t-1}		−0.120	0.008	0.004	0.266	0.249	0.271	0.232
		(1.08)	(0.07)	(0.03)	(6.05)***	(5.45)***	(7.74)***	(5.31)***
$\Delta\log(S)^* gov_{t-1}$			−5.837	−5.482	−2.501	−3.179	−2.649	−3.030
			(5.06)***	(4.71)***	(1.10)	(1.68)	(1.82)*	(2.89)***
$\Delta\log(E)$				0.059		0.073		0.090
				(0.98)		(1.43)		(1.84)*
$\log(SDP_{t-1})$	−0.092	−0.093	−0.098	−0.105	−0.009	−0.004	−0.005	−0.001
	(5.43)***	(5.40)***	(5.80)***	(4.77)***	(1.06)	(0.57)	(0.68)	(0.09)
1970s	0.017	0.018	0.015	0.018	0.005	0.009	0.001	0.005
	(2.80)***	(2.74)**	(2.74)**	(3.30)***	(0.70)	(1.18)	(0.17)	(0.65)
1980s	0.032	0.033	0.031	0.033	0.013	0.014	0.010	0.011
	(4.89)***	(4.75)***	(5.45)***	(5.11)***	(1.71)*	(2.06)*	(1.42)	(1.80)*
1990s	0.071	0.072	0.069	0.075	0.035	0.038	0.031	0.034
	(6.24)***	(6.15)***	(6.05)***	(5.31)***	(4.05)***	(4.36)***	(3.93)***	(4.70)***
Observations	84	84	84	78	84	78	84	78
(within) R-squared	0.59	0.59	0.62	0.64	0.41	0.45		

Note: Heteroskedasticity-robust t-statistics are in parentheses.
*** Indicates significance at 1%.
** Indicates significance at 5%.
* Indicates significance at 10%.

columns (3) and (4), we use the fixed effects panel estimator, which allows us to control for unobserved state-fixed effects. We also follow other papers in the growth literature (e.g. Barro and Lee, 1994; see also the Monte Carlo evidence in Hauk and Wacziarg, 2009) by employing the seemingly unrelated regressions (SUR) estimator. The advantage of the SUR estimator (results reported in columns 5 and 6) is that it allows for different within-state correlations of the error term across different states. The results in Table 3 indicate that the baseline findings are robust to using different estimators. Further, whether we exclude electricity growth (columns 1, 3, and 5) or include it (columns 2, 4, and 6) does not alter the main findings significantly.

The key result to take away from the regression of SDP growth on education growth presented in Table 3 is that there is no significant association between education growth and SDP growth. We will tackle endogeneity concerns below, but note already that a possible omitted variables bias is likely to lead to a positive correlation between education growth and unobserved shocks to economic growth, thus leading to an upward bias. Thus, insignificant results on education growth can probably not be explained by omitted variables bias. Together with the existence of high returns to education in India, which are documented for example in Psacharopoulos (1994), the baseline findings therefore indicate that the micro–macro puzzle that the literature describes based on cross-country data also exists within India.

4.2. *The role of government*

The theoretical considerations of Section 3 above suggest that an interaction term between government size and human capital growth should be included in the regression framework. A negative interaction term could be seen as support for the hypothesis that the government sector has absorbed much of the human capital in unproductive positions or even in positions that exert a negative impact on the state's private sector. Table 4 presents the first set of results for regressions that include government sector size variables. The proxy for government sector size, *gov*, is government employment as a percentage of the working age population (at the beginning of the decade). Note that government employment figures are not available for all states, so baseline results (i.e. as in column 3 of Table 3) are repeated in this table for those states for which government employment numbers are available to make results more comparable across specifications. We again use the same estimators as above and show fixed effects, pooled and seemingly unrelated regressions estimates.

In column 2 of Table 4 the effect of education growth is small in size and statistically insignificant, even after controlling for the linear effect of government sector size. However, once we include the government sector size interacted with education growth (in column 3 and in the following columns), the effect of education growth is positive and statistically significant. Equally important in the context of our two hypotheses, the interaction term itself is negative and significant in the fixed effects and SUR specifications. Note that the interpretation of the coefficient on the education growth variable changes once we include the interaction of education growth with government sector size. It now measures the effect of education growth at a government sector size of zero (which is out of sample). Once again, all results that include government sector size are fairly robust to using different estimators.

In sum, the results in Table 4 support both hypotheses: in the specifications that include the interaction term, educational expansion has a statistically significant positive sign, while the interaction term is negative and significant in all of the fixed effects and the SUR specifications. Thus, we find evidence that suggests that education growth promotes economic growth, but that its effectiveness diminishes as the government sector size increases.

Strictly speaking, the point estimates suggest that education growth has a positive effect if the government sector size is equal to zero. To illustrate the magnitude within sample, consider the effect at the smallest government sector size in the sample: at that size of the government sector - measured relative to the working age population - (namely, where $gov=0.023$), and using the FE, pooled and SUR results in columns 4, 6 and 8 of Table 4, the results imply that moving from the 25th percentile of the education growth distribution (1.7% growth) to the 75th percentile (4.1%), implies an increase in per capita SDP growth of 0.19 percentage points (in the FE specification), 0.24 percentage points (in the pooled specification) and 0.17 percentage points (in the SUR specification).[18]

4.3. Robustness to the use of other measures of capital

As indicated before, state-level physical capital data are unavailable for Indian states. In the regressions above we use data on electricity E as an additional control to proxy for growth in capital inputs. In this section we use information on two important subcategories of physical capital for which we were able to collect data. In particular, we first use a measure of physical capital used in manufacturing. More precisely, our measure is physical capital per person working in manufacturing (K^M), which comes from the EPW Annual Survey of Industries (ASI) database (Economic and Political Weekly Research Foundation, 2002). And, second, we use data on tractors, which we obtain from various issues of the Statistical Abstracts. More specifically, we use the number of tractors per square kilometer (T).[19] Note that both additional variables, capital in manufacturing and tractors, refer to subsectors of a state's economy. In the case of manufacturing this sector is relatively small, especially in the early years of our sample period. The data on tractors could be an indicator of positive changes in the economy, i.e. modernization in agriculture, but more tractors could also be an indicator of lacking progress in a structural transformation from agriculture to other sectors. With this in mind, but also because data on electricity use are available for the majority of our state/year observations, while the other two variables discussed here are not available for as many state/year observations, we focus on electricity as our preferred measure of capital and regard the regressions below as indicative of the robustness of the main results.

The results of these robustness checks are in Table 5. Column 1 is the baseline, using only electricity as a measure of capital. Regressions reported in columns 2 and 3 use data on manufacturing capital and tractors instead of electricity, while columns 4 and 5 additionally also control for electricity. Overall, these regressions confirm the main results qualitatively. The schooling growth variable enters positively, and the interaction term between schooling growth and government sector size is negative. In the two regressions that include capital in manufacturing the estimates for the parameters of interest are now statistically insignificant. It should be noted, though, that generally the number of observations drops when we use the two alternative capital proxies. Even more of a caveat is the fact that capital stock in manufacturing is unavailable for 1961, so the estimates using this capital variable are based on a maximum of three growth observations, which may explain the lower precision of the estimates and the differences in the point estimates. The tractors variable is negative in the regressions, and in one even statistically significantly so, which suggests that an above-average growth in tractors in a particular state may indicate that the structural transformation from agriculture to industry and services is progressing more slowly than in other states, and therefore is associated with lower SDP growth.

4.4. System GMM results

The previous subsections have established that (a) in the standard regression framework of many cross-country regressions, economic growth is not significantly related to schooling growth at the state-level in India, and (b) that this finding changes once government sector size is taken into account. The estimators used so far have the advantage that they allow for a direct comparison of the present results to other influential papers in this literature, e.g. Krueger and Lindahl (2001). In this and the following two subsections, we show that this finding is largely robust to dealing with the likely endogeneity of government sector size, as well as the possible endogeneity of schooling growth and other variables. We do so employing the system GMM estimator. This estimator will also take into account the endogeneity of y_{t-1}, the initial level of SDP per capita (in the presence of autocorrelation of the errors), as well as the possible endogeneity of the growth of electricity use, $\Delta\log(E_t)$.

[18] A note on the effect of the pure government size is in order: in specifications that do not include the interaction the parameter estimate for government size indicates an insignificant effect of government size. On the other hand, the significant parameter estimates for the government size variable in some of the specifications that include interaction terms need to be interpreted in the same way as the education growth variable, i.e. together with the interaction term. Thus, the significant parameter estimates imply simply that if education capital growth is equal to zero, government size is significantly positively correlated with SDP growth. However, as pointed out, education growth is significantly larger than zero for most state/decade observations.

[19] Using tractors *per capita* we obtain similar results.

Table 5
Robustness to other measures of capital: capital in manufacturing and tractors.

	(1)	(2)	(3)	(4)	(5)
$\Delta\log(S)$	0.206	0.779	0.210	0.754	0.212
	(1.79)*	(0.79)	(2.74)**	(0.76)	(2.22)**
gov_{t-1}	0.004	0.183	−0.064	0.132	−0.205
	(0.03)	(0.40)	(0.40)	(0.29)	(1.46)
$\Delta\log(S)$*gov_{t-1}	−5.482	−17.854	−5.913	−16.353	−4.440
	(4.71)***	(0.94)	(5.99)***	(0.86)	(3.86)***
$\Delta\log(E)$	0.059			0.040	0.049
	(0.98)			(0.54)	(0.73)
$\Delta\log(K^M)$		−0.025		−0.019	
		(0.80)		(0.48)	
$\Delta\log(T)$			−0.035		−0.099
			(0.73)		(2.19)**
$\log(\mathrm{SDP}_{t-1})$	−0.105	−0.134	−0.102	−0.132	−0.114
	(4.77)***	(4.50)***	(3.69)***	(4.42)***	(4.22)***
1970s	0.018		0.013		0.019
	(3.30)***		(1.93)*		(2.58)**
1980s	0.033	0.020	0.031	0.018	0.035
	(5.11)***	(4.03)***	(4.03)***	(3.77)***	(3.86)***
1990s	0.075	0.066	0.073	0.066	0.098
	(5.31)***	(5.62)***	(3.75)***	(5.39)***	(4.98)***
Constant	0.303	0.400	0.307	0.396	0.345
	(4.87)***	(3.94)***	(3.75)***	(3.89)***	(4.53)***
Observations	78	63	67	61	64
(within) R-squared	0.64	0.65	0.60	0.67	0.68

Note: Fixed effects results are shown; heteroskedasticity-robust *t*-statistics are in parentheses.
*** Indicates significance at 1%.
** Indicates significance at 5%.
* Indicates significance at 10%.

To deal with endogeneity, the system GMM estimator (Blundell and Bond, 1998) uses instruments that are derived from past observations of the endogenous variables. The Blundell and Bond (1998) estimator combines the idea of Arellano and Bond (1991), namely using lagged values (dated $t-2$ and earlier) in levels as instruments for the differenced variables in the equation in first-differences, with the idea of Arellano and Bover (1995), namely using lagged first-differences to instrument endogenous variables in the equations inn levels. Combining these two equations results in a system of equations, which is simultaneously estimated, thus this estimator is also known as the "system GMM" estimator. One necessary condition for this approach to be valid is that error terms in differences do not follow an AR(2) or higher order process, an assumption which we test and cannot reject in any of our results. For a fuller description of the system GMM estimator, including a description of the implementation in Stata that we use for our empirical work, see Roodman (2006).

Our specification treats $\Delta\log(S_t)$, $\Delta\log(S_t)*gov_{t-1}$ and $\Delta\log(E_t)$ as contemporaneous endogenous variables, and y_{t-1} and gov_{t-1} as predetermined. Thus, the included instruments for the difference equation are (1) lags of y_{t-1} and gov_{t-1}, and (2) lags of the *lagged* values of $\Delta\log(S_t)$, $\Delta\log(S_t)*gov_{t-1}$ and $\Delta\log\,(E_t)$. For the levels equation instruments are (1) differences of y_{t-1} and gov_{t-1}, and (2) differences of the *lagged* values of $\Delta\log(S_t)$, $\Delta\log(S_t)*gov_{t-1}$ and $\Delta\log(E_t)$.

Because in a system GMM there are many possible instruments, which can lead to biased estimates, it is imperative to restrict the number of instruments (Roodman, 2009; Tauchen, 1986; Windmeijer, 2005). Here we use different approaches to restrict the number of instruments. Table 6 reports the results; for all specifications we report the resulting number of instruments in the table. The first approach uses the above mentioned instruments for the difference equation lagged one period and, for the levels equation, the first-difference dated t; this regression (in column 1) is labeled "first lag". An alternative way to restrict the number of instruments is to use deeper lags. Column 2 shows results from using the above mentioned instruments for the difference equation lagged two and three periods, and first-differences dated $t-1$ and $t-2$ for the levels equation (labeled "second and third lag"). This approach further restricts the number of instruments significantly because deeper lags are not available for all variables. Column 3 only uses the second lag (i.e. $t-2$ for the difference equation and first differences dated $t-1$ for the levels equation). We also use the collapsing strategy as suggested in Roodman (2009). More specifically, we collapse the matrix of instruments related to predetermined variables, those regressions are labeled "collapse" (in columns 4 and 5).[20] In column 5, the restriction on lags and the collapsing are combined. In none of the regressions can we reject the over-identifying restrictions, supporting the validity of the instruments. The *p*-value of the Hansen test, which is equal to 0.984 when we use all 37 available instruments (results not reported), goes down to between 0.4 and 0.8 in most regressions when we restrict the number of instruments, lending

[20] In unreported results, we additionally collapse the matrix of instruments related to the contemporaneous endogenous variables. This specification pushes the restriction on the number of instruments so far that all the parameter estimates are imprecise.

Table 6
System GMM results.

	(1) First lag	(2) Second and third lag	(3) Second lag	(4) Collapse	(5) First lag + collapse
$\Delta\log(S)$	0.045	1.295	1.454	0.007	0.221
	(0.22)	(1.79)*	(1.98)*	(0.02)	(0.63)
gov_{t-1}	0.287	0.595	0.687	0.275	0.196
	(10.93)***	(2.12)**	(2.35)**	(3.14)***	(1.29)
$\Delta\log(S)*gov_{t-1}$	−5.214	−15.968	−18.672	−7.418	−6.117
	(4.21)***	(1.37)	(1.91)*	(1.46)	(1.07)
$\Delta\log(E)$	0.177	0.114	0.114	0.108	0.122
	(2.18)**	(0.58)	(0.69)	(0.50)	(0.86)
$\log(SDP_{t-1})$	−0.018	−0.036	−0.032	−0.007	−0.007
	(1.39)	(1.12)	(1.24)	(0.40)	(0.52)
1970s	0.002	0.062	0.062	−0.014	0.008
	(0.13)	(1.99)*	(1.90)*	(0.43)	(0.21)
1980s	0.010	0.068	0.072	−0.006	0.015
	(0.87)	(2.04)*	(2.05)*	(0.17)	(0.45)
1990s	0.034	0.107	0.106	0.012	0.035
	(2.10)**	(2.53)**	(2.56)**	(0.27)	(0.90)
Constant	0.047	0.008	−0.009	0.038	0.011
	(1.20)	(0.11)	(0.14)	(0.69)	(0.16)
Observations	78	78	78	78	78
Number of instruments	28	20	18	27	20
Test for AR(2) in first differences (*p*-value)	0.668	0.231	0.175	0.905	0.982
Hansen test of overid restrictions (*p*-value).	0.971	0.344	0.458	0.733	0.745

Notes: Estimates from two-step difference GMM with the Windmeijer (2005) correction. *t* statistics clustered by state are in parentheses. The second row indicates the approach to reduce the number of instruments; for details see the text.

*** Indicates significance at 1%.

** Indicates significance at 5%.

* Indicates significance at 10%.

support to the concern about too many instruments and the need for a restriction of the set of instruments as we implement it here.

Once again, the findings that (a) economic growth is positively related to schooling growth, and (b) that the interaction term between schooling growth and government sector size is negative, are mostly robust. However, for both findings the caveat needs to be added that the t-statistics are somewhat smaller in some of the IV-regressions relative to the fixed effects and SUR regressions reported in the previous sections, and the point estimates show a larger variation across specifications. The analyses in the next two sections, in which we exclude the public administration's contribution to SDP, and also show specifications in which we adjust the schooling data for possible differences in education quality, will demonstrate the robustness of both fixed effects and GMM estimates further.

4.5. Excluding the public administration's contribution to SDP

A potential concern of our analysis thus far is that the contribution of the government sector to SDP is measured at factor prices. For labor inputs in this sector we hypothesize that factor prices are larger than marginal products. Therefore growth in the total amount of wages paid in the government sector will lead mechanically to growth of SDP, although the measure that we are interested in, output, might not change, or at least not change as much as SDP at factor prices changes. To address this concern directly, we exploit the fact that our data allow us to exclude the public administration's contribution to SDP from the total SDP measure. Keeping all other measures as in the previous table, i.e. relative to the working-age population, we find that results do not change significantly if we exclude the public administration's contribution to SDP from the SDP growth calculations; these results are reported in Table 7. In column 1 results are analogous to the key fixed effects regression from Table 5, while columns 2–4 repeat regressions 1, 4, and 5 of Table 6 with this new SDP measure. We find only small differences, and several estimates are even stronger (i.e. the interaction is more significantly negative) when we use the alternative SDP measure.[21]

[21] This statement is also true if the regressions are run on the same samples. (The results in the tables presented here are not strictly comparable because sample sizes differ slightly because of missing public administration SDP data.)

Table 7
Excluding the public administration's contribution to SDP.

	(1) FE	(2) System GMM	(3)	(4)
		First lag	Collapse	First lag + collapse
$\Delta\log(S)$	0.350	0.218	0.309	0.557
	(2.03)*	(0.45)	(1.15)	(0.70)
gov_{t-1}	−0.005	0.342	0.275	0.290
	(0.03)	(5.93)***	(2.36)**	(1.86)*
$\Delta\log(S)*gov_{t-1}$	−8.308	−7.718	−6.761	−7.574
	(4.54)***	(2.88)***	(2.11)**	(1.28)
$\Delta\log(E)$	0.038	0.121	0.021	0.066
	(0.59)	(1.75)*	(0.14)	(0.51)
$\log(SDP_{t-1})$	−0.110	−0.017	−0.001	−0.006
	(5.09)***	(1.71)*	(0.07)	(0.37)
1970s	0.022	0.001	0.008	0.019
	(3.31)***	(0.04)	(0.37)	(0.31)
1980s	0.036	0.006	0.014	0.026
	(5.61)***	(0.16)	(0.64)	(0.47)
1990s	0.078	0.030	0.035	0.049
	(6.24)***	(0.66)	(1.15)	(0.68)
Constant	0.312	0.041	−0.006	−0.015
	(4.96)***	(1.07)	(0.15)	(0.20)
Observations	76	76	76	76
Number of instruments		28	27	20
Test for AR(2) in first differences (*p*-value)		0.985	0.754	0.683
Hansen test of overid restrictions (*p*-value)		0.454	0.362	0.635

Notes: Column (1): Fixed effect estimates, Columns (2)–(4): Estimates from two-step difference GMM with the Windmeijer (2005) correction. *t* statistics clustered by state are in parentheses. The second row indicates the approach to reduce the number of instruments; for details see the text.

*** Indicates significance at 1%.

** Indicates significance at 5%.

* Indicates significance at 10%.

4.6. Can alternative arguments explain the results?

4.6.1. Education quality

Next, we consider the possibility that differences in the quality of education explain the results. It might be that schooling quality is heterogeneous in India and the variable "years of schooling" is a measure of educational attainment that is not directly comparable across Indian states. The significant interaction term could result if it were true that (a) educational attainment is a poor measure of human capital (which is concerned with both quantity and quality of education) and at the same time (b) the extent of the disconnect between educational quantity and education quality is correlated with government sector size. To investigate the above-mentioned possibility, we investigate (a) the correlation of years of education with measures of education quality that we have available, and (b) the correlation of government sector size with the available measures of education quality. Overall, in unreported results, we find that average years of education in a state are positively correlated with various measures of schooling quality, and changes in average years of schooling are positively correlated with changes in measures of schooling quality in a state.[22] On the other hand, the correlation of government sector size and schooling quality is less strong.[23] In sum, we find evidence against the potential concern raised above.

Despite the results of the above correlation analysis, as a further robustness check, we take differences in education quality explicitly into account in the econometric analysis by calculating quality-adjusted schooling measures. To adjust schooling for quality differences in each census year, we multiply the average years of schooling variable by the teacher-student ratio, where

[22] We can make use of the following proxies for schooling quality: (i) educational expenditure, (ii) numbers of teachers, both using data from Statistical Abstracts (Central Statistical Organization, various years), (iii) recent measures on teacher absenteeism from Kremer et al. (2005), and (iv) data that were collected in 2006 by an NGO that tests children for reading and math skills at the household level (Pratham, 2007). Note that only the first two proxies are available with a panel dimension. Full results are available from the authors.

[23] We find, as would be expected, a significant correlation between government sector size and education-related spending per pupil. We also find a strong correlation between government sector size and the total number of teachers per student. However, we do not find a correlation between the absenteeism data (from Kremer et al., 2005) and government sector size. The correlation coefficient between government sector size and the variable "teachers being present and teaching" is 0.007 (with a *p*-value of 0.97). Similarly, there is no correlation between government sector size and the other two absenteeism variables – "teachers absent" and "teachers present but not teaching". On the other hand, the correlation coefficient between "years of education" and "teachers being present and teaching" is 0.507 (*p*-value 0.03) and there is a significant (negative) correlation between years of education and the other two absenteeism variables, "teachers absent" and "teachers present but not teaching".

Table 8
Using quality-adjusted education figures.

	(1) FE	(2) System GMM	(3)	(4)
		First lag	Collapse	First lag + Collapse
$\Delta \log(S^q)$	0.282	0.398	0.503	0.597
	(2.27)**	(2.02)*	(2.08)**	(1.36)
gov_{t-1}	−0.112	0.283	0.292	0.278
	(0.74)	(2.36)**	(3.48)***	(1.91)*
$\Delta \log(S^q)$*gov_{t-1}	−4.202	−2.873	−4.541	−5.954
	(3.63)***	(1.58)	(2.37)**	(1.55)
$\Delta \log(E)$	0.019	0.104	−0.095	−0.019
	(0.27)	(1.00)	(0.50)	(0.12)
$\log(\text{SDP}_{t-1})$	−0.103	−0.024	−0.007	−0.005
	(4.85)***	(1.63)	(1.24)	(0.51)
1970s	0.025	0.024	0.015	0.019
	(3.95)***	(2.18)**	(1.46)	(0.76)
1980s	0.038	0.030	0.025	0.028
	(5.69)***	(2.50)**	(2.75)**	(1.08)
1990s	0.080	0.055	0.047	0.047
	(6.36)***	(4.15)***	(4.27)***	(1.61)
Constant	0.289	0.033	0.000	−0.013
	(4.70)***	(0.76)	(0.02)	(0.60)
Observations	76	76	76	76
Number of instruments		28	27	20
Test for AR(2) in first differences (p-value)		0.478	0.391	0.338
Hansen test of overid restrictions (p-value)		0.798	0.840	0.648

Notes: Column (1): Fixed effect estimates, Columns (2)–(4): Estimates from two-step difference GMM with the Windmeijer (2005) correction. t statistics clustered by state are in parentheses. The second row indicates the approach to reduce the number of instruments; for details see the text.

*** Indicates significance at 1%.

** Indicates significance at 5%.

* Indicates significance at 10%.

higher ratios suggest higher quality.[24] This measure is used as the quality adjusted schooling measure, S^q, for the results reported in Table 8. For these regressions we continue to use the SDP measure that excludes the public administration's contribution to SDP. It should be noted that this procedure to adjust for schooling quality is somewhat ad hoc and makes some assumptions about substitutability between quality and quantity. However, since the correlation analysis in the previous paragraph shows that the years of education variable is indeed correlated with other measures of quality, we have reasons not to be too concerned about heterogeneity in schooling quality and therefore we do not investigate this further with alternative specifications.

Again, the main results (Table 8) regarding the schooling variables and their interaction with government sector size are quite robust. In fact, the system GMM results are now somewhat stronger, since the estimates are now statistically significant for the schooling growth variables in two of the three GMM specifications. Repeating the earlier calculations for a state with the smallest government sector size in the sample, moving from the 25th percentile to the 75th percentile of the education growth distribution implies an increase in per capita SDP growth of 0.4 percentage points based on the FE estimates in column 1, and 0.8 percentage points, 1 percentage point, and 1.1 percentage points, respectively, based on the estimates in columns 2, 3, and 4.[25]

4.6.2. Labor market regulation

Previous research has shown the importance of labor market regulation in India (Besley and Burgess, 2004). One might expect that the type of regulation (pro-worker versus pro-employer) is correlated with the size of government, and it could therefore be that size of government just proxies for the type of regulation. In unreported analyses, we have investigated this possibility and tested for an alternative way in which the general political regime may have influenced under what circumstances education is effective, namely through labor market regulation. Note that, in principle, both pro-worker and pro-employer regulation could imply a larger bureaucracy and that educated individuals in the government sector are employed in low productivity jobs (and thus implying a negative interaction term between education growth and government sector size), even if just one type of regulation has a direct negative impact on growth. Using the measure (at

[24] While we do not have direct measures of education quality, following our previous argument we could proxy quality with either expenditure per student or teacher-student ratios. Since expenditure is directly related to SDP, we focus on the teacher-student ratio.

[25] At the mean of government sector size (3.9%), this effect is between 0.28 and 0.86 percentage points. At the maximum (18.4% - in Delhi), this effect is between −0.3 and −1.2 percentage points.

the beginning of each decade) of labor market regulations from Besley and Burgess (2004), who study state-level amendments to the Industrial Disputes Act of 1947, we cannot find statistically reliable evidence for an interaction between regulation and schooling effectiveness. Most importantly, the education growth variable is not a statistically significant positive predictor of SDP growth; indeed, the coefficient is mostly (statistically insignificant) negative.[26]

4.6.3. Migration

Another potential concern is whether migration between Indian states could explain the findings. The answer, in our view, is no: first, migration is generally considered to be low in India, especially with respect to the – here relevant – cross-state migration. Secondly, the state-level measures of human capital are based on census data which record the level of education in a particular state at the time of the census. Thus, unlike in cases where education capital is calculated based on enrollment numbers, if migration across state borders occurs and the location in which education is received and education is used differ, census data will pick up these effects.

4.6.4. Teachers as government employees

Government employment includes teachers who work for the public sector. This may partly explain the positive coefficient of government sector size in the cross-state regressions. In addition, it seems reasonable to hypothesize that the impact of education growth would vary with the number of teachers. However, we hypothesize that the effect of education growth should be larger, the more teachers there are, because this will likely improve the quality of education. Thus, the fact that teachers are included in our government sector numbers will work in the opposite direction of what we find.[27]

5. Conclusion

Education frequently takes center stage in discussions about economic development. Indeed, at the micro level, the positive effects of education for human and social development, including effects on health and wages, have been widely documented. However, at the macro level, the empirical evidence on the relation between education growth and economic growth is mixed. This paper investigates this puzzle, which so far has mainly been investigated using cross-country regressions. One contribution of this paper is therefore to employ instead within-country variation to investigate how educational expansion could have failed to promote economic growth in an economy, India, with a substantial wage premium for education. Our key contribution is to suggest and test a hypothesis that may reconcile the findings at the micro and the macro levels. We hypothesize that in India part of the explanation of the micro–macro puzzle can be found in the relationship between the large public sector and the rest of India's economy: the public sector employed the majority of educated workers at high wages, but this allocation of India's human capital failed to promote substantial growth because of the limited productivity of educated workers thus employed.

The theoretical framework suggested in this paper generates a testable hypothesis, and we present evidence that is consistent with this hypothesis: the data indicate that the effect of government sector size on education's effectiveness in promoting growth was negative, economically large, and statistically significant. This suggests that government absorbed human capital in low productivity activities. Once we control for this effect of government sector size on educational effectiveness, the results indicate that the effect of education in India was positive and significant for a wide range of Indian states with relatively low levels of government. At the smallest government sector size in the sample the results imply that moving from the 25th percentile of the education growth distribution to the 75th percentile implies an increase in per capita SDP growth of between 0.2 percentage points[28] and 1.1 percentage points.[29] This positive effect of human capital growth is not only restricted to states with the smallest government sector size: We find that 95% of state/year observations have a government sector small enough such that they would experience a positive SDP growth effect from an increase in human capital growth.[30]

Can we say something more positive about the contribution of education to growth in India after the significant reforms that India underwent in the 1980s and early 1990s? First, note that in light of the dramatic improvement of economic performance in the years after 1980, one might suspect educational expansion to have begun to have a more positive effect on economic growth. We do not have enough state-level data to reliably perform pre- and post 1990 comparisons that allow us to test for statistical differences between those periods. However, the micro-evidence on public–private wage differentials shows that large positive wage differentials between the public and private sectors persisted through the

[26] A previous version of this paper that includes the full results of the analyses reported in this subsection is available from the authors.

[27] To get a sense of the share of teachers in the government sector, data from 1996 can be used. According to a report (Government of India, 2002), the group of "Professional, technical and related workers", which contains teachers, is the second biggest occupational division that the report lists, constituting 28.5% of all public sector employees (Government of India, 2002, p. 7). Within the group of "Professional, technical and related workers", teachers account for 54.4%. Thus, overall, in 1996 teachers make up about 15% of all public sector employees. Because of privatizations and other reform activities in the 1980s and 1990s, this share is likely to be larger than it was in earlier time periods, for which precise data are not available.

[28] This number is based on the simplest FE specification.

[29] This number is based on the system GMM specification that uses quality-adjusted education measures and SDP measures net of the public sector contribution.

[30] This number is also based on the system GMM specification that uses quality-adjusted education measures and SDP measures net of the public sector contribution.

1990s, with the public sector wage premium being up to 140%. Thus, on average, it seems that outside opportunities for educated workers were still unattractive relative to the opportunities provided by the state bureaucracy, but according to our findings would have had significant social returns in terms of economic growth.

The results suggest that private and social returns to education are vastly different in India and suggest that the effects of the misallocation of human capital in India were significant. Despite many issues that may be unique to India's situation, the analysis may also provide a lesson for other developing nations in which the public sector constitutes a particularly large fraction of the formal economy. This may, in the end, help reconcile economists' and policy makers' priors on the central role of education in the development process with the empirical evidence.

Appendix A. Micro evidence on public–private wage differentials and returns to education

To provide evidence on public–private wage differentials and returns to education at the state level we perform additional analyses using National Sample Survey (NSS) micro data. Every five years the National Sample Survey Organization uses an additional questionnaire (schedule 10) with detailed information on employment. We can use data from 1993 (Round 50) and 1999/2000 (round 55) to provide state-level evidence.[31] We estimate the public–private differential using Mincer-type regressions as follows:

$$\log(wage) = \alpha + \beta\ public + \gamma S + \delta_1 age + \delta_2 age^2 + \delta_3 male + \delta_4 urban + \varepsilon$$

here *public* is the public ownership dummy variable, S is years of schooling, and *male* and *urban* are gender and urban/rural indicator variables, respectively. In addition, we also estimate a public–private differential for individuals with at least secondary education, by adding to the above specification an indicator variable, *secondary*, which is equal to one if the individual has secondary education or above, and the interaction of *secondary* and *public*. A public–private differential for holders of graduate degrees is estimated analogously.

In results that are not reported here in detail[32] we find that the public–private wage ratio estimated from the 1993 (round 50) data ranges between approximately 1.2 and 1.7. Once other individual characteristics are controlled for, the estimated public sector premium is between 33% in the full sample and 22% for holders of graduate degrees. We also analyze the public–private differential by state and find that in almost all states individuals in the public sector are paid more than individuals in the private sector. Only for one state (Mizoram) we consistently find estimates of the public–private wage ratio that are smaller than one. We find very similar results using the Round 55 data.

Appendix B. Data construction

Data on government sector employees (that include central government employees, state government employees, quasi-government employees, local body government employees) as well as on total employment come from several series of books published by India's Central Statistical Organization. The data from 1961 come from Statistical Abstract of the Indian Union 1962. Data from 1971 were unavailable, so data from 1972 were substituted; they come from Statistical Abstract 1972. Data for 1981 come from the Statistical Abstract 1982. Data for 1991 were also unavailable, and the closest available data were from 1988; these come from Statistical Abstract 1992. Government population share was computed by dividing the total number of government employees by the working age population, i.e. the number of individuals with ages between 15 and 59.

Data from 1996 are available to provide some information about the occupational pattern of employees in the government sector (Government of India, 2002): According to this report, the government sector includes the following occupational divisions: "Clerical & related workers", this group constituted 31.6% of all public sector employees (Government of India, 2002, p. 7), "Professional, technical and related workers" (28.5%), "Production and related workers, transport equipment operators and laborers (21.6%), "Service Workers" (12.1%), "Administrative, executive & managerial workers" (3.9%), "Farmers, Fisherman, hunters, Loggers and related workers" (1.9%), and "Sales workers" (0.4%).

Data on levels of education in each state and year come from the various censuses of India for 1961, 1971, 1981, 1991, and 2001 (see Registrar General and Census Commissioner of India, several years). These data were used to construct the estimates for average years of education as well as average primary years of education, average secondary years of education, and average higher years of education, from which the human capital growth numbers were computed. To compute average years of education, it was assumed that primary education corresponded to five years of education, middle education corresponded to eight years of education, and secondary education corresponded to ten years of education. A degree corresponded to thirteen years of education, a professional degree corresponded to fourteen years of education, a medical degree corresponded to fourteen and a half years of education, and vocational education corresponded to eleven and a half years of education. These estimates come from the web documents "Secondary Education," "Higher Education in

[31] Unfortunately, earlier NSS rounds do not contain information that allows researchers to identify whether individuals work for a public or a private employer. To be able to say something about earlier years, we also resort to an analysis of enterprise-level data from the Annual Survey of Industries (ASI). The estimated public–private wage differential in the manufacturing sector ranges from 50% to about 130% over the 1980 to 2000. Full results and derivation of these results are available from the authors.

[32] Full results, including results broken down by state, are available from the authors.

Table C1
Summary statistics.

Variable	Observations	Mean	Standard deviation
$\Delta\log(\text{SDP})$	84	0.023	0.021
$\log(\text{SDP}_{t-1})$ (Rs., base year 1973)	84	3.010	0.367
$\Delta\log(S)$	84	0.040	0.039
ΔS	84	0.115	0.067
gov_{t-1} (=government employees/population aged 15–59)	84	0.052	0.031
I{decade=1960s}	84	0.202	
I{decade=1970s}	84	0.226	
I{decade=1980s}	84	0.274	
I{decade=1990s}	84	0.298	

Note: Restricted to core sample (as used in Tables 3 and 5); all values relative to working age population (15–59 years old).

India," and "Technical Education" published by India's Department of Education (see Department of Education, no year a–c, online resource). To compute average years of education, total years of education were computed by summing the total number of persons with primary education times the years of primary education and the total number of person with secondary education times the number of years of secondary education, etc., for each year and state. Total years of education were then divided by the total working age population, also from census data, to compute average years of education.

SDP per capita data come from the following sources: For 1961 and 1971 SDP data come from Özler et al. (1996). The data for 1981, 1991, and 2001 come from the website of India's Ministry of Statistics and Programme Implementation (see Ministry of Statistics and Programme Implementation, no year a, b, online resource). The data on the public administration's contribution to SDP for the years 1961 and 1971 come from Economic and Political Weekly Research Foundation (2003). SDP data were corrected for inflation using the CPIIW (G) deflator with base year 1973, which is provided by Özler et al. (1996) for years up to 1991. The deflator for data from 2001 was calculated using data from the website of India's Labor Bureau (Labor Bureau, Government of India, no year). The electricity variable used in the analysis ($\log(E)$) is electricity sold to ultimate consumers (measured as the logarithm of million kilowatt hours per capita). The tractors variable used in robustness checks ($\log(T)$) is electricity sold to ultimate consumers (measured as the logarithm of tractors per square kilometer). The data is from various issues of the Statistical Abstracts.

Appendix C. Summary statistics

See Table C1.

References

Aghion, P., Burgess, R., Redding, S., Zilibotti, F., 2005. Entry liberalization and inequality in industrial performance. Journal of the European Economic Association 3 (2–3), 291–302.
Aghion, P., Burgess, R., Redding, S., Zilibotti, F., 2008. The unequal effects of liberalization: evidence from dismantling the license raj in India. American Economic Review 98 (4), 1397–1412.
Arellano, M., Bond, S., 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. Review of Economic Studies 58 (2), 277–297.
Arellano, M., Bover, O., 1995. Another look at the instrumental variable estimation of error-components models. Journal of Econometrics 68 (1), 29–51.
Banerjee, A., 2006. The paradox of Indian growth: a comment on Kochar et al. Journal of Monetary Economics 53, 1021–1026.
Bardhan, P., 1984. The Political Economy of Development in India. Basil Blackwell, New York.
Barro, R., 1991. Economic growth in a cross-section of countries. Quarterly Journal of Economics 106 (20), 407–443.
Barro, R., Lee, J., 1993. International comparisons of educational attainment. Journal of Monetary Economics 32 (3), 363–394.
Barro, R., Lee, J., 1994. Sources of economic growth. Carnegie-Rochester Conference Series on Public Policy 40, 1–46.
Behrman, J., 1987. Schooling in developing countries: which countries are the over- and underachievers and what is the schooling impact? Economics of Education Review 6 (2), 111–127.
Benhabib, J., Spiegel, M.M., 1994. The role of human capital in economic development: evidence from aggregate cross-country data. Journal of Monetary Economics 34, 143–173.
Besley, T., Burgess, R., 2004. Can labor regulation hinder economic performance? Evidence from India. Quarterly Journal of Economics 119 (1), 91–134.
Blaug, M., Layard, R., Woodhall, M., 1969. The Causes of Graduate Unemployment in India. Allen Lane The Penguin Press, London.
Blundell, R., Bond, S., 1998. Initial conditions and moment restrictions in dynamic panel data models. Journal of Econometrics 87 (1), 115–143.
Bond, S.R., Hoeffler, A., Temple, J., 2001. GMM estimation of empirical growth models. CEPR Discussion Papers 3048.
Caselli, F., Esquivel, G., Lefort, F., 1996. Reopening the convergence debate: a new look at cross-country growth empirics. J. Econ. Growth 1, 363–389.
Central Statistical Organization, India. Statistical Abstract of the Indian Union. Government of India Press, New Delhi, various years.
Cohen, D., Soto, M., 2007. Growth and human capital: good data, good results. Journal of Economic Growth 12 (1), 51–76.
de la Fuente, A., Doménech, R., 2006. Human capital in growth regressions: how much difference does data quality make? Journal of the European Economic Association 4 (1), 1–36.
Department of Education, India, no year a. Higher Education in India. Online resource, ⟨http://www.education.nic.in/higedu.asp⟩.
Department of Education, India, no year b. Secondary Education. Online resource, ⟨http://www.education.nic.in/htmlweb/secedu.htm⟩.
Department of Education, India, no year c. Technical Education. Online resource, ⟨http://www.education.nic.in/tecedu.asp⟩.
Economic and Political Weekly Research Foundation. 2002. Annual survey of industries, 1973–74 to 1997–98: a data base on the industrial sector in India.
Economic and Political Weekly Research Foundation, 2003. Domestic Product of States of India: 1960-61 to 2000-01. Mumbai.

Economic and Political Weekly Research Foundation, 2004. National Accounts Statistics of India, 1950-51 to 2002-03: Linked Series with 1993–94 as the Base Year. 5th edition. Mumbai.
Gelb, A., Knight, J., Sabot, R., 1991. Public sector employment, rent seeking and economic growth. Economic Journal 101 (408), 1186–1199.
Government of India, 2002. Occupational-Educational Pattern of Employees in India: Public Sector 1996. Directorate General of Employment & Training, Ministry of Labour, New Delhi.
Hauk, W., Wacziarg, R., 2009. A Monte Carlo study of growth regressions. Journal of Economic Growth 14, 103–147.
Heckman, J., Klenow, P., 1997. Human Capital Policy. Manuscript.
India, Office of the Registrar General, 1975. Census of India 1971. Series 1, India. Part VII(i)_(ii): Degree Holders and Technical Personnel, New Delhi.
Jaimovich, E., Rud, J.P., 2012. Excessive Public Employment and Rent-Seeking Traps. Manuscript, University of Surrey.
Kremer, M., Muralidharan, K., Chaudhury, N., Rogers, H., Hammer, J., 2005. Teacher absence in India: a snapshot. Journal of the European Economic Association 3, 658–667.
Krueger, A., Lindahl, M., 2001. Education for growth: why and for whom? Journal of Economic Literature 39, 1101–1136.
Labor Bureau, Government of India, no year. Centre-wise Consumer Price Index Numbers (General) for Industrial Workers. Online resource, ⟨http://labourbureau.nic.in/CPI%20IW%202004%20Table%203%20P.htm⟩.
Lucas, R., 1988. On the mechanics of economic development. Journal of Monetary Economics 22 (1), 3–42.
Mincer, J., 1974. Schooling, Experience, and Earnings. Columbia University Press, New York.
Ministry of Statistics and Programme Implementation, India, no year a. State Domestic Product. Online resource ⟨http://www.mospi.nic.in/⟩.
Ministry of Statistics and Programme Implementation, India, no year b. Net State Domestic Product (1993–94 Series). Online resource: ⟨http://www.mospi.nic.in/⟩.
Mukhopadhyay, M., Parhar, M. (Eds.), 1999. Indian Education: Developments Since Independence, Vikas Publishing House, New Delhi.
Murphy, K., Shleifer, A., Vishny, R., 1991. The allocation of talent: implications for growth. Quarterly Journal of Economics 106 (2), 503–530.
Özler, B., Datt, G., Ravallion, M., 1996. A Database on Poverty and Growth in India. Policy Research Department, World Bank, Mimeo.
Panchamukhi, P.R., 1996. Educational Change in India. Har-Anand Publications, New Delhi.
Pandey, R., 1992. National Policy on Education in India. Horizon Publishers, Allahabad.
Pratham. 2007. Annual Status of Education Report 2006 (Rural). Online resource, ⟨http://www.pratham.org/aser2006.php⟩.
Pritchett, L., 2001. Where has all the education gone? World Bank Economic Review 15 (3), 367–391.
Pritchett, L., 2006. Does learning to add up add up? The returns to schooling in aggregate data. In: Hanushek, E., Welch, F. (Eds.), Handbook of the Economics of Education, vol. 1. , North-Holland, Amsterdam, pp. 635–695. (Chapter 11).
Psacharopoulos, G., 1994. Returns to investment in education: a global update. World Dev. 22 (9), 1325–1343.
Raveendran, G., 2006. Estimation of Contribution of Informal Sector to GDP. Paper presented at the "Expert Group on Informal Sector Statistics", New Delhi.
Registrar General and Census Commissioner of India. Census of India, years: 1961, 1971, 1981, 1991, 2001.
Rogers, M., 2008. Directly unproductive schooling: how country characteristics affect the impact of schooling on growth. European Economic Review 52, 356–385.
Roodman, D., 2006. How to do xtabond2: an Introduction to "Difference" and "System" GMM in Stata. Working Paper 103. Center for Global Development, Washington.
Roodman, D., 2009. A note on the theme of too many instruments. Oxford Bulletin of Economics and Statistics 71 (1), 135–158.
Sivadasan, J., 2003. Barriers to Entry and Productivity: Micro-Evidence from Indian Manufacturing Sector Reforms. Manuscript, Graduate School of Business, University of Chicago.
Tauchen, G., 1986. Statistical properties of generalized method-of-moments estimators of structural parameters obtained from financial market data. J. Bus. Econ. Stat. 4 (4), 397–416.
Temple, J., 1999. A positive effect of human capital on growth. Economics Letters 65 (1), 131–134.
Temple, J., 2001. Generalizations that are not? Evidence on education and growth. European Economic Review 45, 905–918.
Topel, R., 1999. Labor markets and economic growth. In: Ashenfelter, O., Card, D. (Eds.), Handbook of Labor Economics, vol. 3C. , North-Holland, Amsterdam, pp. 2943–2984.
Trivedi, K., 2006. Educational human capital and levels of income: evidence from states in India, 1965–92. Journal of Development Studies 42 (8), 1350–1378.
Windmeijer, F., 2005. A finite sample correction for the variance of linear efficient two-step GMM estimators. Journal of Econometrics 126 (1), 25–51.