Academic specialization and returns to education: Evidence from India

Bibhas Saha[a] and Rudra Sensarma[b]

[a] School of Economics, University of East Anglia, Norwich, NR4 7TJ, UK

[b] Business School, University of Hertfordshire, Hatfield, Herts, AL10 9AB, UK

Abstract

We study returns to academic specialization for Indian corporate sector workers by analyzing cross-sectional data on male employees randomly selected from six large firms. Our analysis shows that going to college pays off, as it brings significant incremental returns over and above school education. However, the increase in returns is more pronounced in the specializations of management and engineering, and less so in the specializations of science, arts and commerce. Some of the less attractive specializations, like commerce and science, tend to make up by rewarding progression from Bachelors to Masters. Short-course Diplomas are also rewarding.

JEL Classification: J01; O12

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1. Introduction

Traditionally earnings studies relate earnings to total years of schooling - a standard measure of human capital - and other observable characteristics. See Schultz (1988) for a survey of the earlier literature, Psacharopoulos and Patrinos (2004) for a global update on returns to education and Heckman, Lochner and Todd (2003) for emerging issues in the literature. It has now been recognized that years of schooling capture only the time dimension of human capital, and fail to identify any vertical or horizontal differentiation that may be present between any two individuals with the same years of schooling. The vertical difference may reflect a *quality* hierarchy which can be measured by educational test grades or tiers of specialization completed (such as Bachelors or Masters), whereas the horizontal differentiation reflects different *types* of human capital that can be identified with different specialization of studies. In many contexts, the type of human capital may become more important than the number of years of education. For this reasons, corporations where a large number of employees are hired with diverse types of skills and specializations provide a natural context where returns to schooling can be studied at a much broader dimension.

The number of papers on returns to academic specialization is relatively few and that too mostly for the developed countries; but the evidence wherever available is clear: specialization matters. In the context of the US most studies show that natural science and business specializations contribute significantly to higher returns than humanities and social sciences for both men and women (see Berger (1998), Rumberger and Thomas (1993), and Arcidiacono (2004)). Similarly, for Canada, it has been observed by Finnie and Frenette (2003) that for both males and females the returns to studying health, engineering, sciences and commerce are higher than that from arts and humanities.

Dolton and Vignoles (2000) noted for the UK that engineering and technical education provided higher returns for the first job but specialization ceased to matter six years after graduation. Machin and Puhani (2003) showed that for both UK and Germany specializations constitute about 24-40% of the explained earnings and explain between 8 to 20% of the gender gap in wages. For Northern Ireland McGuiness and Bennett (2007) found that for women the returns to specializing in medical science and technology are greater than that in social science.

In the context of India, there are few earnings studies available that take into account specialization. Duraisamy and Duraisamy (1993) were the first to study returns to scientific and technical education. They observed that between men and women the returns were considerably higher for the latter. But they could not say whether this specialization was more rewarding over other specializations, because their data were confined only to individuals with scientific and technical specialization. In a later study using the census data of 1971 and 1981 Duraisamy and Duraisamy (1996) compared the mean earnings across specializations. They found that the mean earnings of engineering graduates were 1.3 to 1.5 times that of humanities graduates; but due to the aggregative nature of the data further analysis was not possible. There is no other study for India, as far as we know, that has accounted for detailed specialization. Nevertheless, almost all Indian studies share a common result: college education is rewarding, and this finding appears to be robust over the last forty years or so, as evidenced by different studies that relied on cross-sectional data at different points of time. The above mentioned two studies relate to 1971 and 1981. Saha and Sarkar (1999) have reported a similar finding from a 1987 dataset. Then Dutta (2006) has used three datasets from 1983, 1993-94 and 1999-2000, and Bhandari and Bordoloi (2006) used a 2004-05 dataset, both confirming that the marginal rate of returns to education is much higher at the college level.

Given the overwhelming evidence of stable and high returns to higher education, it seems imperative to get a sense of returns to specialization. But there is a serious problem of data availability. In this paper, we use a 1987 dataset drawn from six large Indian firms[1], which contains detailed information on employees' education, earnings and firm-specific experience. This dataset was originally collected and studied by Saha and Sarkar (1999).[2] Though the data seem to be somewhat dated, it is a unique dataset where one can study the returns to specialisation in the context of India. Such detailed information for Indian workers on years spent in pursuing different academic specializations as our dataset provides is not available from any secondary source or even from large surveys such as the National Sample Surveys or census data. Further, as the employees in our dataset belong to the same or similar firms, we have a natural control on work environment and certain labour market characteristics. For example, all these workers are subject to similar labor and industrial regulations that may affect their earnings. All may have some part of their salaries negotiated by their unions, as is often the case in large Indian firms. Having a mixture of formal and informal sector employees or small and large firm employees can bring in additional issues of labor market segregation which are important in developing country contexts. Our dataset allows us to abstract from these problems. At the same time, being extremely diversified and large, the six firms we consider employ a wide cross-section of skilled personnel that is fairly representative of the educated workforce of the country.[3]

[1] These firms are publicly traded large business houses and were among the top ten firms in terms of annual turnover during the study period.
[2] The source of the data was company annual reports, which up to 1987 contained detailed data on employees above a cut-off income level. A change in regulation led to disappearance of this dataset from the public domain after 1987.
[3] Ideally one should have longitudinal data for such studies. But for India the national household survey data are not longitudinal. Moreover, rarely do we find precise information on education, income and work experience from such surveys. One could get such data from the firm sources as public limited companies were required to disclose employee details, and 1987 was the last year to obtain this data. After 1987 a change in the regulation allowed firms to report the details of their managerial staff only. Building a panel data going back several years prior to 1987 proved difficult.

Though the dataset belongs to 1987, our chosen companies are still among the top manufacturing companies in India, and they have maintained their dominant position over the last thirty years. None has undergone major changes like takeovers, large-scale downsizing or loss of a product range. This is in conformity with the continuity of India's manufacturing sector as a whole, unlike the newly emerged information technology or services sectors. Looking from the education side, management and technology are still among the most sought after study disciplines in India, as was the case thirty years ago. This trend has not changed; if anything, the trend has become stronger. Therefore, the potential insight to be gained by analyzing this 1987 data can be helpful even today, though admittedly the policy environment has changed.

We estimate returns to specialization (in five categories) and also at different tiers of higher education, such as Bachelors and Masters. Our main finding is that academic specialization matters meaning that the marginal rate of returns to college education is strictly positive. But there is also a hierarchy among specializations meaning that the specializations matter in different degrees. Management education comes on top followed by engineering and commerce[4] which are at the bottom. As for moving from Bachelors to Masters within a specialization, there are no returns except in two less attractive specializations – science and commerce. However our work is limited by the absence of information on individual ability (e.g. high school grades or IQ test scores). To that extent our results for returns to education may be influenced by unobserved ability. In this sense the rates of returns to specialisations are overestimated. Moreover our regression approach only reflects the association of a particular academic specialization with higher or lower earnings and does not

[4] Commerce specialization in India largely involves studying accountancy and book-keeping, and does not go into business management issues. This in turn helps commerce graduates to start careers in accounting firms, tax consultancy and related services, whereas management graduates aim for junior managerial positions in the corporate sector.

explicitly test for causality from education to earnings. We provide a detailed discussion of our findings later in the results section.

Here we would like to distinguish our work from that of Saha and Sarkar (1999) as we use the same dataset. Saha and Sarkar were mainly concerned with the trade-off between returns to education and returns to work experience and so they modelled education simply in terms of the schooling years ignoring specialization. In contrast, our primary focus is on the differences between distinct specializations within college education, which has been largely ignored in the growing earnings literature on India. See for instance, Tilak (1987), Duraisamy and Duraisamy (1998), Kingdon and Unni (2001), Duraisamy (2002) and the articles cited earlier. Even though study periods and coverage varied, all these studies confirm the importance of college education, but do not go far enough to identify returns to specialization. We try to fill this gap.[5]

The paper is organized as follows. Section 2 discusses the data and Section 3 presents the empirical analysis. The results are discussed in Section 4 followed by concluding remarks.

2. Data and the average age-earnings profile

Our data are collected from the annual reports of six large Indian private sector firms for the financial year April 1986 to March 1987. All public limited companies, as per regulations in India, were required to publish details about employees whose gross annual earnings exceed a certain level. In 1986-87, the cutoff earnings level was Rs. 36000.[6] We address the sample selection bias due to

[5] Our period of analysis falls in between the study periods of Duraisamy (2002) – i.e. between 1981 and 1991. When combined with other studies our work may help us to understand how the Indian industry valued higher education in the run up to large scale economic reforms undertaken in 1991, after which the economy moved to a higher growth path.
[6] In 1986-87, the exchange rate was roughly $1 = Rs. 15.

this income cut-off in our estimation methodology. The details of the information include, name of the employee, sex, age, date of joining the present firm, educational degrees, total number of years worked before joining the firm, and gross and net (after income tax deductions and pension contributions) earnings for the current year.

The six firms that we selected were among the largest in India in terms of turnover for that year, and they have been maintaining their strong positions for over two decades. They were (and still are) highly diversified firms producing a wide range of products such as textiles, cement, automobiles, steel and providing construction and engineering works. Their offices and production facilities are located all over India. They attract a wide range of workers from across the country. While in the cement and textile sector one may find less educated (e.g. school drop-outs) workers (such as spinners, pourers and fitters), in the automobile and engineering sector there may be highly educated workers coming from the country's premier engineering colleges.[7] From each company a random sample of 10% of the employees was chosen and the female workers, being very few in number, were excluded from our analysis. This left us with a sample of 3327 workers.[8]

Like any other developing country, India's labor market is dualistic. The share of industry in total employment is only about 20%, and within the industrial sector there is a very large informal sector.[9] Our study relates only to the formal industrial sector, within which public sector firms and multinationals also play significant roles. The hiring practice of public sector firms is not too different from the large private sector firms (except for some affirmative action policy). However,

[7] Our results mostly capture features of the Indian corporate sector and may not relate to hiring practices of other sectors such as small and medium enterprises.
[8] The raw data was available only in hard copy. Compiling a large dataset with all the employees proved too costly. Hence a 10% sample was decided upon.
[9] The definition of informal sector is loose. Generally firms that are small and are outside a number of work-related regulations fall in this category.

during our study period the presence of multinationals in India was minimal. Therefore, caution should be used in extrapolating our results to foreign firms and small firms. Subject to these qualifications, we believe our data will be representative of the formal industrial sector as a whole.

A bird's eye view of the data is presented in Table 1. As is evident from the average age of the workers, the sample consists largely of middle aged workers. This is due to the fact that we could observe only those workers whose earnings exceeded a certain level. However, in terms of years of schooling, the workforce appears to be fairly educated. The average years of schooling for the sample of 3327 workers are 11.63 years. However, as the wide gap between the minimum (1 year) and the maximum (22 years) suggest, we do have a wide cross section of individuals. This is also true for age and earnings. The average (gross annual) earnings are Rs. 51374. This figure is near the minimum (Rs. 36000) and far below the maximum (Rs. 267000). Indeed in our sample, entries with earnings in excess of Rs. 150000 are fewer. Apart from the variations in the data, our large sample size of over three thousand observations is also likely to contribute to the robustness of the estimates.

(Table 1 about here)

Given the primary information of main degrees and additional diplomas or degrees of the individuals in our data sources, we have converted them into schooling years. Secondary schooling means 10 years, higher secondary 12 years,[10] Bachelors (non-engineering) 15 years, Masters 17 years,

[10] However, prior to 1980 in many states of India higher secondary meant 11 years of schooling, and engineering undergraduate studies were 5 years long. Such discrepancies were gradually eliminated between 1977 and 1987. Therefore, we had to choose a cutoff year and make adjustments in the years of schooling. This led us to assign 11 years of schooling to higher secondary, if the individual was older than 27 years at the time of our study. For higher education we have used the programme durations that are standard across colleges in India. However, there might be some odd exceptions which remained unaccounted for. Thus, for older workers Bachelors would mean 14 years of educations and Masters 16 years of education.

engineering Bachelors 16 years and engineering Masters 18 years.[11] Lastly, for most diplomas, we have not assigned any years on the ground that diplomas can be acquired as a trainee or part-time student.[12]

Having defined the schooling years, we obtain its distribution and mean age and earnings for each of the schooling levels in Table 2a (without counting the diplomas). Note that the distribution of schooling years is bi-modal and well spread out. There are two concentration points, one between 10 and 12 years and the other at 16 years of schooling. More than 50 percent of the workers in our sample have secondary or higher secondary education. At 13 years of schooling which refers to incomplete college education, the distribution sharply falls, but then it reaches another height at 14 (Bachelors or incomplete Bachelors; see footnote 10) and 16 (Masters and engineering Bachelors combined, see footnote 10). The last two categories account for 24 percent of the workforce. A further disaggregate picture is presented with respect to specializations in Table 2b. As can be seen 58.10% of the sample consists of workers having higher education or having completed school and acquired a diploma. Among them 28.55% are diploma holders (majority of which are in engineering), and the remaining employees are evenly spread out among Arts, Science and Engineering, while Management claims a small share – only 1.23%. The small share of Management is explainable by the pyramid structure of employees, with few managers on top.

(Tables 2a and 2b about here)

[11] We have a handful of cases of PhD or similar post-Masters education; however they have been clubbed with the category Masters.

[12] We assumed that individuals did not take any break from their education. It is quite uncommon in India for students to take time off from their school or college education. Because of a persistent problem of oversubscription in most colleges, fresh applicants are always admitted in preference to applicants with interrupted schooling. However, after admission some students might have to repeat a year. As long as this proportion is small our results remain unaffected.

3. The model

Our starting point is a basic Mincer earnings function:

$$\ln y_i = c + \alpha s_i + \beta_1 x_i + \beta_2 x_i^2 + \gamma_1 z_i + \gamma_2 z_i^2 + u_i \qquad (1)$$

where y_i is annual earnings of individual i, s_i is his years of schooling, x_i the work experience (in years) in the current firm which we call tenure[13], z_i the past work experience (prior to joining the current employer) and u_i is a random error term which is assumed to be normally distributed with zero mean and σ^2 variance. We then introduce dummy variables to distinguish academic specializations in higher education – such as arts, science, commerce etc. This gives us:

$$\ln y_i = c + \alpha s_i + \sum_{j=1}^{5} \gamma_j S_{ji} + \sum_{j=1}^{3} \mu_j D_{ji} + \beta_1 x_i + \beta_2 x_i^2 + \gamma_1 z_i + \gamma_2 z_i^2 + u_i \qquad (2)$$

Here, S_j is a dummy variable for the *j*-th specialization in university (which refers to degrees in five fields of study[14], namely, arts, commerce, science, engineering and management). The excluded category covers those employees who did not have college or university education. In India while the universities award degrees, there are polytechnics or specialized training colleges that award diplomas based on short courses in various fields suitable for part-time students. We include such diplomas as well. D_j refers to *j*-th diploma dummy and there are three diplomas – engineering, management and social studies. The excluded category is for no diploma and a range of different diplomas which are neither management, nor engineering. Note the difference between diplomas and specialization dummies. Though both can be in the same field diploma dummies refer to qualifications acquired at polytechnics, while the specialization dummies pertain to degrees obtained from a university.

[13] Tenure may capture effects of on-the-job learning, training and firm-worker matching. In the absence of additional information we cannot separate out these possible effects.
[14] Arts refers to humanities, and not fine arts.

We include both diplomas and degrees (i.e. specializations) as the number of individuals having one or the other is significantly high. To be specific, 983 workers (or 30% of observations) hold degrees but do not have diplomas (please see table 2b for the distribution). On the other hand 950 workers (or 29% of observations) have diplomas but not university degrees. For instance in case of engineering, 277 workers have an undergraduate (BTech) degree in engineering (out of whom 37 went on to acquire postgraduate degree i.e. MTech) but these workers do not have an engineering diploma. There were 708 engineering diploma holders who do not have a degree in engineering. Therefore, by including both subject specialism and diploma dummies in the same regression we will be able to compare the effects that these different qualifications have on earnings.

Finally the schooling variable is modified and introduced as spline variables (linear splines denoting the number of years spent in studying the relevant specialization at a particular level), which allows us to capture the branching out of individuals in different specializations (in their higher studies) and at the same time directly measure incremental rate of returns to such specialized education. Diplomas are also taken into account, but they appear as dummy variables.

Thus the final model becomes:

$$\ln y_i = c + \alpha_1 s_{1i} + \alpha_2 s_{2i} + \sum_{j=1}^{5} \alpha_3^j s_{3i}^j + \sum_{j=1}^{5} \alpha_4^j s_{4i}^j + \sum_{j=1}^{3} \mu_j D_{ji} + \beta_1 x_i + \beta_2 x_i^2 + \gamma_1 z_i + \gamma_2 z_i^2 + u_i \qquad (3)$$

Here, the spline variables are defined as follows: s_1 refers to schooling up to the secondary level, s_2 higher secondary, s_3^j Bachelors study with *j*-th specialization, s_4^j refers to Masters with *j*-th specialization and D_j refers to j-th diploma dummy. The specializations and diploma categories are as described earlier.

We provide a caveat that specialisation may be highly correlated with 'ability', because high ability workers may be sorted out early on by channelling them into different academic specialization, and in the absence of any control for ability (such as high school grades or IQ test scores), returns to specialization may also capture in part returns to ability as well. While in India high 'ability' students are generally encouraged to appear for highly competitive entrance exams for management and engineering education, it is equally conceivable that a student may 'prefer' to specialize in science or social science than 'engineering' even if she is perfectly capable of doing well in the latter. In the absence of any data on individuals' innate ability, we accept that our estimates may include returns to ability and thus upwardly bias the returns to specialization. That said, it is reasonable to assume that the bias, if it exists, would be systematic leaving the relative ranking of specializations in terms of returns unaffected.

An important point in the context of estimating our model is that we cannot use the Ordinary Least Square (OLS) regression method for the fact that in our sample we do not observe workers whose annual gross earnings were below Rs.36000. As the distribution of earnings is truncated, the OLS estimates will be biased and inconsistent. We therefore use maximum likelihood (ML) estimation with truncated distribution to address the sample selection bias.

Consider the case where we observe the true dependent variable $ln\ y_i^*$ as $ln\ y_i$ only when it exceeds a threshold level, say $\underline{y}$. This can be represented as:

$ln\ y_i^* = X_i\beta + u_i,$

$ln\ y_i = ln\ y_i^*\ if\ y_i^* > \underline{y}$

where X_i is a vector of explanatory variables, β is the vector of unknown parameters to be estimated and u_i is a normally distributed error term with mean 0 and variance σ^2.[15]

Under this specification, the likelihood function based on which the ML estimates are obtained is given by:

$$L_i = \frac{1}{\sigma}\left[\phi\left(\frac{\ln y_i - X_i\beta}{\sigma}\right)\right] \Bigg/ \left[1 - \Phi\left(\frac{\ln \underline{y} - X_i\beta}{\sigma}\right)\right]$$

To test for significance of the coefficient estimates, robust standard errors are employed using the Huber-White sandwich estimator.

4. The Results

The estimates of equation (1) are shown in Table 3 in two panels, one without firm controls and the other with firm controls.[16] All the explanatory variables have the expected signs. In the first panel (without firm controls) the rate of returns to schooling is 8 percent, while the same to tenure (experience in the current firm) and past experience (experience in previous firms) are 5.5 percent and 4.7 percent respectively. Both of these experience components exert concavity as is commonly seen in such studies. It is noteworthy that education yields higher returns than tenure, and tenure higher than past experience. This is consistent with other Indian studies such as Duraisamy and

[15] Admittedly our results are subject to validity of the strong distributional assumptions and the log linear functional form. However we feel it is reasonable to assume a normal distribution in case of our large sample and the log linear form as is a common practice in similar econometric studies.
[16] All estimations were done in Stata (release 11).

Duraisamy (1996) and Duraisamy (2002). We can compare our estimates with that of Duraisamy and Duraisamy (1996) for their 1981 data where for the male workers the rates of returns to education and experience were 5.9 percent and 5.3 percent (their Table 5, p.52), and with that of Duraisamy (2002) for his analysis of 1993-94 data which is reported by education level in his Table 3 (p.616). Rate of returns to work experience in these two studies (though they correspond to different time periods) is in the order of 5.3 to 6 percent, fairly close to ours.

In the second panel we report the estimates with firm controls. As can be seen, rate of returns to schooling and tenure both improve marginally, but returns to past experience fall. Compared to the benchmark firm (firm 6), all firms except one (firm 1) have significant effects on earning.

(Table 3 about here)

Now we add dummy variables for academic specialization into equation (1) and these estimates are shown in Table 4, again in two panels - without firm controls and with firm controls. There are five dummy variables for five fields of specializations for graduate studies – arts (i.e. humanities), science, commerce, engineering and management. We also include short-course diplomas (which are one-year or two-year long) – engineering, management and social study. The dummies are all significant, except for arts and commerce (see the first panel). However, the returns to schooling marginally fall (as compared to Table 1), as the specialization dummies separate the effects of years of education from the field of education. It is noteworthy that management degree dummy has a higher coefficient than any other degree dummies, followed by engineering and science, highlighting the attractiveness of management as a field of education. For diplomas also management is most rewarding. This picture remains intact even after we control for firm-specific effects (second panel). Somewhat curiously the coefficient of management dummy falls and the gap between management and engineering is narrowed down a bit. Similar is the case with engineering and management diplomas, though in this case coefficients rise for both of them.

Finally, we estimate equation (3) where education is modeled as a sequence of spline variables reflecting individuals' branching out in different specializations (conditional on reaching college) and progressing to higher tier of specialization. As said earlier, tier of study captures vertical differentiation of human capital, while specialization captures horizontal differentiation.

Table 5 reports the results of this regression. Consider the estimates reported in the first panel. First of all, the rate of returns to secondary schooling is 6.4%, which then rises to 8.2% with the completion of the higher secondary education. Second, this rate of return is even bettered with college education, as the incremental return from Bachelors study in any specialization is positive and significant. That is to say, higher education is rewarding. Further, rate of returns to Bachelors study is different across specialization giving rise to a hierarchy that is consistent with common perception and it also refines the stylized fact on higher education in India emerging from the earnings literature discussed earlier. Social studies in general fare poorly compared to scientific and technical studies. Bachelors study in management yields an incremental return of 15.4 percent per annum as compared to 12.4 percent for engineering, 6.3 percent for science, 5.1 percent for arts and 2.6 percent for commerce. Compared to the 8.2% rate of return to the higher secondary level, the returns are much higher for management and engineering, but lower for other specializations, and in particular it is noticeably so for commerce.

Third, for commerce and science, the loss in the marginal rate of return is more than compensated by progressing to Masters. Progressing to Masters is most rewarding for science, generating an incremental return of 9.8%, while for commerce -- the only other category where it is statistically significant -- it is 7.5%. In the case of arts and management, the additional returns are statistically insignificant but positive – 1.9% for arts and 12.1% for management. This means that even though the estimates are not reliable in a statistical sense, Masters study in these two specializations also brings some additional returns which are however smaller in comparison with Bachelors study. Finally in the case of engineering Masters study might actually reduce earnings. This might reflect a negative perception of postgraduates in engineering. Progression to Masters might indicate that the person was unable to find a placement immediately after her Bachelors degree which is the standard acceptable qualification in engineering in India. However, even here the Masters coefficient is statistically insignificant. Thus, we see that vertical differentiation is not always rewarding. Masters might be regarded as academic training more geared towards research, and industries that do not focus on R&D (as is typically the case in developing countries) may not be willing to pay a premium for such degrees.

Fourth, the above point is indirectly corroborated by the significance of short-course diplomas, which are exclusively geared towards industry needs. The estimates reveal that engineering and management diplomas significantly add to earnings, relative to individuals having no diplomas. Here too management tops the list followed by engineering. We should note that the value of the intercept parameter is 9.169. A management diploma alone adds 0.08 to it and an engineering diploma adds 0.063 to it. A social study diploma adds only 0.05 but it is not statistically significant.

On the second panel we include firm dummies. As before Firm 1 is not significant and the specialization hierarchy remains unchanged. However, except for Bachelors in science and commerce, coefficients for all other Bachelors specializations slightly fall; for Bachelors in science and commerce the coefficients actually rise. For diplomas on the other hand, the coefficients increase for both management and engineering. As in Table 4, here too the gap between management and engineering gets narrower when firm controls are taken into account.

(Table 5 about here)

5. Conclusion

The literature on returns to education has paid scant attention to the issue of academic specialization and quality hierarchy therein. This is more so for developing countries. This paper has tried to fill this gap by using a dataset from India. We find that college education is rewarding, but its returns vary depending on the specialization. Management and technical fields generate higher returns than general streams (science, commerce and arts). But we do not always find progression from Bachelors to Masters rewarding; it is rewarding only for those specializations, which are at the lower order of the specialization hierarchy. This suggests that vertical skill differentiation may not be as important as horizontal skill differentiation. These observations are robust, as we control for firm specific effects, current firm experience and past experience.

The above findings may help us understand why Indian industries have been able to grow in high technology sectors in recent times. The growth in technology sectors may reflect demand-side factors, policy changes and global opportunities. However the history of rewarding higher education also played some role in ensuring adequate supply of technical skills which were necessary to support the growth. While this might have caused significant earnings inequality among the labor force between skilled and unskilled, educated and less educated, and between the formal and informal sectors, the policy makers should see such inequalities in proper perspective. High returns to technical specializations may reflect the Indian industry's strategy to improve its productivity.

There are some limitations of our study that we need to be cautious about while generalizing our findings to Indian industry today. First, in recent time multinational firms and specialized Indian outsourcing firms have emerged as equally significant employers of educated workers along with the traditional manufacturing firms. While this trend is likely to enhance returns to technical and management education both, their relative importance might change due to the influence of overseas markets. Second, our study did not include women; therefore, we could not say anything about gender inequality. It remains to be seen, if academic specialization can explain gender gap, or if there is reverse gender gap within some specializations. Third, our estimates for returns to education are subject to the functional form we have employed for the Mincer equation and the distributional assumptions of the maximum likelihood estimation. Fourth, our results may not necessarily extend to the broader Indian economy specifically to the informal sector and small firms. They are only indicative and need to be treated with caution in relation to other sectors. Fifth, owing to a lack of control for individual ability, our returns to specialization estimates may have an upward bias. As might be expected, higher ability students go to university and possibly even choose more attractive specializations. Hence, some of the higher returns may reflect ability and motivation, which we have omitted due to lack of information. Sixth, the standard regression approach we have employed can only examine the association between specialization and earnings and cannot provide any causal interpretation. Finally, there are some measurement issues (such as the exact years associated with each spline variable) that could not be effectively dealt with due to lack of information. Nevertheless, our study provides a benchmark with which new studies can be contrasted to see to what extent economic reforms and globalization have benefitted the educated Indian workers.

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Table 1: Summary Statistics

Variable	Mean	Minimum	Maximum
Earnings (Rs.)	51374	36000	267000
Schooling (yrs.)	11.63	1.00	22.00
Age (yrs.)	41.94	22.00	69.00
Total experience (yrs.)	19.20	1.00	47.00

Table 2a: Schooling years, mean age and earnings

Schooling (years)	% in total sample	Mean age (years)	Mean earnings (Rs.)
8	1.35	43.00	42821
9	9.67	46.54	45516
10	29.11	43.00	48275
11	10.69	41.73	48890
12	12.80	39.30	49593
13	1.47	42.00	49854
14	11.11	42.65	53387
16[a]	7.75	38.30	65615
16[b]	5.47	37.20	60220
17	5.47	39.49	65215
18	1.50	37.90	61681

Note: [a] refers to engineering undergraduate, [b] refers to Masters in general studies.

Table 2b: Distribution of specializations

	Numbers	% of total		Numbers	% of total
School and no higher education	1394	41.90			
Higher education	1933	58.10			
of which BA	168	5.05	BA and MA	79	2.37
of which BCom	219	6.58	BCom and MCom	83	2.49
of which BSc	278	8.36	BSc and MSc	107	3.22
of which BTech	277	8.33	BTech and MTech	37	1.11
of which BBA	41	1.23	BBA and MBA	41	1.23
of which Diploma	950	28.55			
Engineering Diploma	708	21.28			
Management Diploma	158	4.75			
Social study Diploma	84	2.52			

Note: The figures for higher education reflect degree/ diploma completions.

Table 3: Basic Mincer regressions

	Model without firm dummies			*Model with firm dummies*		
	Coefficient	Standard Error	95% Confidence Interval	Coefficient	Standard Error	95% Confidence Interval
Schooling	0.080**	0.004	0.0724, 0.0878	0.082**	0.003	0.0755, 0.0886
Tenure	0.055**	0.004	0.0477, 0.0628	0.059**	0.004	0.0517, 0.0654
Tenure-square	-0.001**	<0.001	0.0011, -0.0007	-0.001**	<0.001	-0.0011, -0.0008
Past Exp	0.047**	0.003	0.0409, 0.0537	0.029**	0.003	0.0235, 0.0342
Past Exp-square	-0.001**	<0.001	-0.0009, -0.0004	<0.001	<0.001	-0.0003, 0.0002
Firm 1				0.032	0.031	-0.0280, 0.0926
Firm 2				0.364**	0.024	0.3166, 0.4104
Firm 3				0.398**	0.025	0.3486, 0.4474
Firm 4				0.192**	0.036	0.1208, 0.2623
Firm 5				0.098**	0.025	0.0492, 0.1477
Constant	9.020**	0.084	8.8558, 9.1832	8.794**	0.077	8.6440, 8.9440
Number of obs.	3327			3327		
Pseudo LL	1209.121			1489.479		
Wald Chi-Square	578.960			876.200		

Note: The dependent variable is annual earnings in rupees. Schooling is total education years, Tenure is in-job work experience in years and Past Exp is previous work experience in years (before joining the current employer); Firm 1-5 are dummy variables (Firm 6 is the base category); * and ** indicate statistically significant coefficients at 5% and 1% levels respectively.

Table 4: Returns to education with specialization effects

	Model without firm dummies			*Model with firm dummies*		
	Coefficient	Standard Error	95% Confidence Interval	Coefficient	Standard Error	95% Confidence Interval
Schooling	0.059**	0.006	0.0464, 0.0713	0.058**	0.005	0.0478, 0.0679
Arts	-0.044	0.044	-0.1299, 0.0410	-0.041	0.038	-0.1150, 0.0325
Commerce	-0.048	0.040	-0.1267, 0.0301	-0.009	0.033	-0.0732, 0.0560
Science	0.079*	0.036	0.0091, 0.1489	0.151**	0.031	0.0911, 0.2109
Engineering	0.288**	0.040	0.2096, 0.3658	0.285**	0.033	0.2204, 0.3492
Management	0.395**	0.067	0.2629, 0.5268	0.371**	0.057	0.2588, 0.4827
Engineering Dip	0.039*	0.020	0.0002, 0.0769	0.068**	0.016	0.0357, 0.1002
Management Dip	0.098**	0.026	0.0461, 0.1495	0.111**	0.025	0.0615, 0.1605
Social study Dip	0.040**	0.040	-0.0396, 0.1190	0.008	0.035	-0.0604, 0.0767
Tenure	0.056**	0.004	0.0495, 0.0632	0.059**	0.003	0.0531, 0.0657
Tenure-square	-0.001**	<0.001	-0.0011, -0.0008	-0.001**	<0.001	-0.0011, -0.0008
Past Exp	0.047**	0.003	0.0415, 0.0531	0.030**	0.002	0.0256, 0.0350
Past Exp-square	-0.001**	<0.001	-0.0009, -0.0004	<0.001	<0.001	-0.0004, <0.001
Firm 1				0.026	0.028	-0.0286, 0.0808
Firm 2				0.338**	0.021	0.2965, 0.3800
Firm 3				0.386**	0.023	0.3413, 0.4309
Firm 4				0.184**	0.031	0.1236, 0.2448
Firm 5				0.072*	0.023	0.0274, 0.1159
Constant	9.226**	0.087	9.0561, 9.3964	9.032**	0.076	8.8829, 9.1820
Number of obs.	3327			3327		
Pseudo LL	1313.240			1630.900		
Wald Chi-square	793.440			1240.600		

Note: All education variables (except Schooling) are dummy variables (those who did not go to college form the base category); Dip refers to Diploma (no diploma and other diplomas forms the base category); * and ** indicate statistically significant coefficients at 5% and 1% levels respectively.

Table 5: Returns to specialization years

	Model without firm dummies			*Model with firm dummies*		
	Coefficient	Standard Error	95% Confidence Interval	Coefficient	Standard Error	95% Confidence Interval
Secondary	0.064**	0.011	0.0427, 0.0859	0.062**	0.008	0.0466, 0.0778
Higher Secondary	0.082**	0.019	0.0447, 0.1187	0.082**	0.015	0.0515, 0.1115
BA	0.051**	0.014	0.0246, 0.0784	0.048**	0.012	0.0232, 0.0719
MA	0.019	0.021	-0.0225, 0.0601	0.028	0.019	-0.0099, 0.0660
BCom	0.026*	0.011	0.0046, 0.0481	0.036**	0.010	0.0174, 0.0552
MCom	0.075**	0.015	0.0455, 0.1055	0.082**	0.014	0.0535, 0.1098
BSc	0.063**	0.010	0.0425, 0.0831	0.092**	0.009	0.0748, 0.1098
MSc	0.098**	0.020	0.0589, 0.1371	0.077**	0.016	0.0466, 0.1078
BTech	0.124**	0.007	0.1102, 0.1368	0.121**	0.006	0.1102, 0.1328
MTech	-0.033	0.028	-0.0867, 0.0217	-0.026	0.020	-0.0653, 0.0125
BBA	0.154*	0.076	0.0046, 0.3031	0.130*	0.067	-0.0021, 0.2613
MBA	0.121	0.194	-0.2584, 0.5013	0.155	0.171	-0.1808, 0.4912
Engineering Dip	0.063**	0.019	0.0260, 0.1007	0.093**	0.016	0.0608, 0.1252
Management Dip	0.080**	0.028	0.0252, 0.1341	0.094**	0.027	0.0418, 0.1458
Social study Dip	0.050	0.042	-0.0318, 0.1310	0.009	0.036	-0.0620, 0.0809
Tenure	0.057**	0.003	0.0505, 0.0642	0.060**	0.003	0.0543, 0.0667
Tenure-square	-0.001**	<0.001	-0.0011, -0.0008	-0.001**	<0.001	-0.0011, -0.0008
Past Exp	0.047**	0.003	0.0417, 0.0531	0.031**	0.002	0.0260, 0.0354
Past Exp-square	-0.001**	<0.001	-0.0009, -0.0004	<0.001	<0.001	-0.0004, <0.001
Firm 1				0.019	0.028	-0.0356, 0.0733
Firm 2				0.334**	0.021	0.2922, 0.3760
Firm 3				0.381**	0.023	0.3363, 0.4251
Firm 4				0.184**	0.030	0.1243, 0.2434
Firm 5				0.069*	0.023	0.0244, 0.1131
Constant	9.169**	0.120	8.9340, 9.4039	8.987**	0.094	8.8036, 9.1710
Number of obs.	3327			3327		
Pseudo LL	1320.015			1635.922		
Wald Chi-square	893.750			1411.130		

Note: All education variables (except Diplomas) are splines (number of years spent in the corresponding programme); BA, BCom, BSc, BTech, BBA = Bachelors in arts, commerce, science, engineering, management respectively; MA, MCom, MSc, MTech, MBA= Masters in the above specializations respectively; Diplomas are dummy variables; * and ** indicate statistically significant coefficients at 5% and 1% levels respectively.