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How do Technical Education and Vocational Training Affect Labour Productivity in India?

NCAER Skilling India Working Paper

Seema Sangita*

Abstract: Educationists have had long debates on the efficacy of traditional forms of education versus vocational training. Even as India grapples with the challenges of improving the quality of primary and secondary education, there appears to be a policy shift in India, favouring vocational trainings that target the skill development of workers. This paper tries to analyse the impact of two types of technical education—one leading to an engineering degree or diploma and the other, to vocational training in selected fields such as Information and Communications Technology (ICT)— on firms operating in the manufacturing sector in India. A Cobb Douglas production function has been enhanced to incorporate education and training in order to understand the implications of the latter on firm performance. The results show that when a larger number of workers acquire technical education that leads to a degree or diploma in engineering, there is a positive impact on the performance of firms. In contrast, participation in vocational training programmes pertaining to similar disciplines has an insignificant effect on firms.

Keywords: Technical Education, Vocational Education, Skills, Employability, Productivity, Digital Skills, ICT Skills

JEL Codes; J4, J24, O1

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1. Introduction

It is imperative for developing countries with limited resources to evaluate the returns to investment in educational or training programmes. This paper assesses the impact of formal technical education and vocational technical education on the productivity of manufacturing firms in India. The standard approach of returns to education analyses are individualistic in nature, based on Mincerian models that focus on the wages earned by a worker with certain levels of schooling and other forms of education. This paper attempts to take such analysis a step further by trying to understand the impact of education and skills of workforce on the productivity of firms. It is found that higher education at the level of graduation and post-graduation as well as technical education that leads to a degree or diploma have a positive impact on the productivity of a firm. However, vocational training in the fields of computer science and electrical engineering does not seem to influence firm level productivity.

Since the Government of India has been laying an emphasis on skill-based training programmes, it is crucial to assess the efficacy of such programmes. In July 2015, a Skill India campaign was launched for implementation of various schemes like the Pradhan Mantri Kaushal Vikas Yojana, and the National Skill Development Mission, among others. A new Ministry of Skill Development and Entrepreneurship has also been set up. Among various other initiatives, the Ministry states that "The ITI (Industrial Training Institute) ecosystem has also been brought under Skill India for garnering better results in vocational education and training."[1]

The policy emphasis on skills training appears to be a fruitful proposition. However, the question is whether these training programmes actually improve employability and productivity in the economy. This question is relevant for both the demand and supply side of the market of education. Students have to choose whether to opt for general education, technical education or vocational training, while policymakers have to take decisions regarding resource allocation across these forms of education. It may be noted that the role of primary and secondary education cannot be undermined. Effective education at these levels builds a foundation for the productive future of the workers.

This paper focuses on technology-related training among a range of different possible skills. These include the disciplines of computer science and engineering, which are the most connected to the field of Information and Communication Technology (ICT). ICT has been a major facilitator of innovation and improved productivity of nations. It has the potential to transform economies. However, the benefits of ICT can be reaped only with the complementary input of engineering and computing skills. The goal of this research project is to develop an understanding of the linkages between access to workers with technology skills and its effect on the productivity level of firms.

India's software sector has grown by leaps and bounds in the recent past and this has been well documented in academic articles such as Bhatnagar (2006), and in the popular media.[2] Consequently, the demand for software skills has led to a boom in IT and engineering education ranging from high quality technical universities to numerous small private institutions. Further, this has also led to the creation of

[1] http://www.skilldevelopment.gov.in/background.html

[2] http://www.nytimes.com/roomfordebate/2010/11/07/what-obama-can-learn-from-india/why-indias-software-industry-prospers

institutes like the ITI, and several vocational courses that provide training in the fields of electrical, electronic and computer sciences.

However, this study is not just about the ICT sector. The presence of ICT skills can facilitate an improvement in productivity in every other manufacturing industry. This would be possible by using technology to make production processes more efficient, and improve supply chain management and human resource management, among other measures.

While the primary goal of this paper is to assess the impact of technical education vis-a-vis vocational courses in the manufacturing sector, it also pays attention to the foundations of our education system—school level education. A by-product of this paper is the validation of the notion that school education in India is not contributing effectively to the productivity of firms. A report by the Ministry of Human Resource Development (HRD), Government of India, shows that the Gross Enrolment Ratio (GER) in primary education stood at 96.9 in the year 2014-15, and that it steadily declines as the level of education increases. The GER figures are 78.5, 54.2 and 24.3 for secondary, senior secondary and higher education.[3] While ensuring a high level of GER at the school level is commendable, it is a cause for concern that this does not translate into better productivity in the manufacturing sector. Of course, there is likely to be a selection bias—better quality students are likely to opt for higher education, nonetheless, there is an indication that the quality of school education requires attention. Further, the problem with the quality of education at the school level seems to extend itself to vocational training programmes. This paper finds that the workers trained in vocational programmes pertaining to computer science and electrical/electronic engineering do not have a positive effect on firm productivity, unlike their colleagues who have received similar training in formal educational institutes.

One of the main challenges of this research question pertains to data. While India has different databases on the manufacturing sector, including the Annual Survey of Industries (ASI), none of the datasets discuss in detail the characteristics of their workers in terms of their educational attainment and skill sets. On the other hand, a different dataset compiled by the National Sample Survey Organisation (NSSO) has information about the employment and details about skill training undertaken by individuals. Hence, an innovative strategy had to be used in this paper to merge these two datasets for mapping the firms with constructed proxy indicators of the skill levels of their workers. Consequently, there is a limitation of lack of intertemporal data.

The second section of this paper contains a detailed literature review. The third and the fourth sections discuss the data and the corresponding empirical strategy used in this analysis. Finally, the results are presented in the fifth section, followed by a conclusion.

[3] http://mhrd.gov.in/sites/upload_files/mhrd/files/statistics/ESG2016_0.pdf

2. Literature Review

This paper attempts to understand the role of general education, technical education and vocational training in the fields of technology in the context of the performance of firms in the manufacturing sector. An attempt has been made to connect two disparate bodies of literature—one that focuses on the choice of vocational training vis-à-vis general education, and another that discusses the role of technical skills in productivity of firm.

2.1 Vocational and General Education

There has been a long-standing debate regarding the choice between vocational training and general education. Yet, there are limited studies on the connection between vocational education programmes and development, as highlighted by McGrath (2012).

Bennel (1996) has carried out a systematic survey of the existing evidence on the issue of general education versus vocational education in developing countries in response to the World Bank's policy of laying an emphasis on general school education over vocational training. The opponents of vocational training point out that in general, labour market outcomes in terms of earning and employment may be better than vocational training, and in the context of limited resources at hand in developing countries, it may be prudent to focus on general education, which is crucial for improving labour productivity. The advantage of general education is that it offers the worker flexibility in terms of occupational choice. Bennel (1996), while compiling the results of several studies that compare the private and social rate of return on investment in general education and vocational education, finds that the former has a greater rate of return. However, Bennel cautions that there are several limitations of the data and also that these studies do not control for differences in the backgrounds of the students. He then moves on to explore the differences in the earnings of individuals in specific occupations, and one study finds that workers with vocational training comprised 40 per cent of the total workers, on an average, and tended to earn incomes nearly 8–10 per cent higher than their colleagues from academic schools in Israel. Another similar study in Brazil found the difference in earnings to be 16–28 per cent higher for vocational school trainees.

Malamud and Pop-Eleches (2010) try to address this issue with the use of relatively more advanced econometric techniques. There was an educational reform in Romania that resulted in a shift of students from vocational to general education. The selected population was from the same cohort that continued with vocational training and those who made the shift. They find that there is not much of a difference among the two groups in terms of employment, family income or wages. One of their interesting findings is that those with general education were less likely to remain single, indicating a social preference for general education over vocational training.

The literature is relatively sparse when it comes to returns to investment on technical skills. Falck, *et al.* (2016) use the framework suggested by Mincer (1974) to estimate returns to ICT skills across 19 developed economies. Their results show that an increase in ICT skills leads to significantly higher wages. Consequently, the authors conclude that ICT skills may be treated as “the new literacy”. Atasoy (2011) attempts to assess the role of ICT skills on employment probability using data from Turkey. The paper studies various types of ICT skills and concludes that having at least one ICT skill is associated with a 20–30 per cent higher probability of obtaining employment.

Nevertheless, it is difficult to directly apply the results of these studies to India since the context of education for the masses in India may be vastly different from that in other countries.

2.2 Technical Skills and Firm Productivity

There has been some research on the positive effect of Information Technology (IT) investment on firm productivity, but in limited contexts. Bresnahan, *et al.* (2002) was one of the earlier research papers that attempted to understand the interlinkages between IT and skill-biased technical change. This, in conjunction with IT-enabled organisational change, led to a positive effect on labour demand in the United States. Further, Kim (2004) and Basu, *et al.* (2004) find that information technology has a positive influence on firm productivity in Korea and the United States, respectively, but the latter study finds that this may not be applicable in the case of the United Kingdom.

Chaibi, *et al.* (2015) take the literature forward to incorporate ‘e-skills’ into the analysis. They investigate causal links between ICT, e-skills, and the performance of firms, and find that there is a positive impact of ICT usage on the successful implementation of new projects. However, the use of firm level data from Luxembourg shows that there is no relationship between ICT staff and training on a firm’s performance. This is surprising since the ICT inputs require complementary inputs in the form of skills. However, this insignificant result could be due to the quality of the training programmes used in the analysis.

In India, the empirical studies on this theme have so far been limited. Berman, *et al.* (2005) try to assess if there was a skill-biased technical change, using the Annual Survey of Industries (ASI) data. However, they did not focus specifically on ICT skills or ICT-biased technical change. Further, they point to different experiences with skill upgrading in the different states of India. While states like Gujarat turned favourably towards skill upgradation, those like West Bengal lagged behind in the 1990s. And they suggest that “further exploration of skill-upgrading in India may do well to focus on state-specific factors such as differences in infrastructure investment and regulation, and in employment protection legislation”. A more recent work by Commander, *et al.* (2011) undertakes a firm level survey of about 500 firms each in India and Brazil, and finds that Brazilian firms use ICT more intensively than Indian ones. At the same time, ICT capital does influence productivity in both countries. This suggests that there is scope for improving ICT usage in firms in India and consequently, for increasing demand for ICT skills.

There is also a limited understanding of factors that determine the diffusion of ICT. Using Irish firm level data from 2001 to 2004, Haller and Siedschlag (2008) find that firms that are larger in size, younger, fast-growing, skills-intensive, export-intensive and located in capital cities are more successful in adopting and using ICT. Piatkowski and van Ark (2011) point out that the convergence process of transitioning countries towards developed countries would eventually need to depend on the intensive use of ICT in the non-ICT producing sector of the economy. Further, they outline three channels through which ICT influences labour productivity: ICT capital inputs, increase in the Total Factor Productivity (TFP) of the ICT sector, and an economy-wide TFP increase by spill-over effect into the non-ICT producing sectors that use ICT. There is a need to develop our understanding of such processes in the context of India.

Motohashi (2001; 2003) uses Japanese firm-level data to explore the effect of the use of information networks on a firm's productivity using cross-sectional and panel data analysis, respectively. Motohashi (2001) tries to assess the impact of information technology on the productivity of firms using a log-log Cobb–Douglas production function. This study finds that IT networks play an important role in productivity in certain tasks like production, sales, and inventory control systems, and logistics management but not in other aspects like human resource management or management planning system. Further, there is a negative impact on tasks like customer relations and financial transactions. Greenan, *et al.* (2001) carry out a correlation analysis between various ICT and R&D indicators, and the measures of the firm performance of labour productivity, TFP, average wage, and skill composition using French manufacturing and services firms' data. Some of their conclusions indicate that there is a positive relationship between the use of ICT and the productivity of a firm. The use of ICT also decreases the share of production by blue-collar workers in the skill composition of a firm.

2.3 Gaps in the Literature

The specific issue of vocational versus general education has not been explored sufficiently in the literature with respect to India. Given certain unique aspects of India's educational system, it may not be feasible to adapt the conclusions of some of the papers discussed above to policymaking in India. Covering this gap in the literature is critical in terms of evaluating the recent focus by the Government of India towards skill development programmes and vocational training programmes. Further, educational and training programmes may influence an individual's productivity as proxied by wages, but for a broader policy decision, it is imperative to draw the linkages between education and training, and the end goal of improving productivity of the economy. While there is some evidence identifying the effect of technical skills on firm-level outcomes in a couple of developed nations, there is inadequate information about India.

Therefore, this paper aims at covering some of these gaps in the literature by undertaking a comparative analysis of general and vocational training within the context of manufacturing firm productivity in India.

3. Data Description

The firm-level data has been sourced from the Annual Survey of Industries (ASI), which is an annual survey carried out among all the registered factories across the entire country. The data used pertains to two years, 2011–12 and 2013–14. The identification of the sector, industry and products of a firm is based on a system of industrial classification called NIC 2008 and this information is available at a 5-digit level of disaggregation. The ASI data follows an establishment approach, that is, each unit under survey is situated in a single location and the main productive activity accounts for most of the value of the products. This fact is very important for this study, because it facilitates the assumption that the workforce is almost entirely being used in a specific industry as defined by a 5-digit NIC code, and thereby matching of the datasets using this code. A total of more than 1240 5-digit NIC codes have been covered in this dataset. More details about the sampling strategy can be obtained in MOSPI (2016). The ASI dataset has been used to gather information about a firm's performance and various factors that may influence the performance at a firm level, including labour and capital inputs that enter a firm's production process.

It may be noted that the analysis includes all the NIC codes and not merely the ones in the technology sector. The idea is that all the sectors have a scope of improving their production or management processes with the use of technology. And hence, it would be crucial to see how the productivity of firms, regardless of the sub-sector to which they belong, is affected by the presence of workers with technology skills.

However, a major challenge of this study is information about the nature of education and vocational training of the workers of these firms. In this paper, this information has been calculated at the level of the 5-digit NIC code using information from the 68th Round of NSSO. Both the ASI and NSSO datasets provide 5-digit NIC codes in which a firm operates or an individual is employed, and this fact has been exploited in this study in order to match the data across these two datasets. The sample of ASI consists of firms that are registered under the Indian Factories Act of 1948, which defines factories as "…any premises including the precincts thereof (i) Wherein ten or more workers are working or were working on any day of the preceding twelve months, and in any part of which a manufacturing process is being carried on with the aid of power or is ordinarily so carried on, or, (ii) Wherein twenty or more workers are working or were working on any day of the preceding twelve months, and in any part of which a manufacturing process is being carried on without the aid of power or is ordinarily so carried on, but does not include a mine subject to the operation of the Mines Act, 1952, or a railway running shed." On the other hand, the NSSO employment–unemployment survey incorporates information from both registered and unregistered manufacturing units. Hence, as a first step of aligning these datasets, a sub-set of the NSSO data has been selected, which includes individuals whose primary occupation involves working in establishments that have 10 or more workers aided by power or 20 or more workers without the aid of power. This eliminates the sample that is not legally required to register. Next, the data set is matched using two strategies. The first strategy entails using only the NIC codes and second involves a combination of the NIC code and location, that is, the state in which the firm and the NSSO respondents are located. The latter obviously has stricter criteria of matching, and is hence likely to be relatively more accurate. On the other hand, using this process would lead to several observations that remain unmatched, which is why a smaller sample size would be required. Hence, the analysis has used both the approaches of matching.

The 68th Round of the NSSO survey consists of employment and unemployment surveys that provide information about various aspects of the labour force in India. This was a quinquennial round of the all-India household level survey carried out during the period July 2011 to June 2012. The objective of this survey was to gather data concerning various characteristics of the labour force, and hence includes information about individual level education, including both general and vocational education as well as the sector in which the workers are employed at a 5-digit NIC code level.

Although this is a household level survey, it also gathers data on the level of educational attainment of each member of the household. There is general information about educational levels, including illiteracy, literate without formal schooling, different levels of schooling (below the primary, primary, middle, secondary, and higher secondary level), certificate courses, graduate and finally, post-graduate and above levels of education. The data also have information about the attainment of technical education in different fields like engineering, medicine, and agriculture, among others. Further, the respondents of this survey are asked if they have either received or are currently receiving any vocational training, and for those who respond affirmatively, there is a follow up question regarding the field of training, like engineering, leather-related work, textile-related work, photography, and work of a beautician, among others.

Specifically, information about technical education in the fields of technology and engineering has been extracted. The information also pertains to individuals who have a degree or diploma at the below or above the graduate levels in the field of engineering. The limitation here is no clear indication of the branch of engineering. However, any branch of engineering education would involve some training in computer skills. Thereafter, information about those who have attained vocational education in the fields of electrical and electronic engineering and computer sciences has been extracted. The first step of this process is to calculate the number of respondents in a particular NIC code. The numbers of respondents that have a high school education; senior secondary level education; graduate or higher levels of education; technical engineering education and finally vocational education, have also been calculated. The share of each of these categories among those who work in a particular NIC code has also been calculated using this data. Similarly, the shares of workers who have school education, higher education, technical education and vocational education in each NIC code under the first strategy of matching have been calculated. In the second strategy, the same indicates for each combination of a NIC code and a state have been found. Hence, while there is no direct information about the level of education of employees of each firm, proxy indicators have been created of the average level of education for each 5-digit NIC code as well as for each NIC code and state.

It may be noted that this analysis has been undertaken for two years of the ASI data: 2012 and 2014. The NSSO survey was carried out in June 2011–12. The first case is a pure cross-section analysis. However, it may take two years after obtaining a degree, diploma or vocational education to obtain a job and to start contributing effectively to the productivity of the firm. The second case, therefore, incorporates this time lag into this analysis.

However, one limitation of this analysis is the lack of availability of education and vocational training data across time, and hence this study is limited to a cross-section analysis. Further, no information is available about the quality of the programme. It is highly probable that workers who have been educated in high-quality schools, colleges, technical or vocational training institutes would contribute more effectively towards firm performance, but it has not been possible to incorporate this information into the analysis.

4. Econometric Specification

4.1 Baseline Model

The econometric specification is based on a Cobb–Douglas Production function (Cobb and Douglas, 1928). Biddle (2012) describes the historical evolution of this approach to study individual firm productivity using the Cobb–Douglas production function. Paul Douglas carried out several empirical studies in the late 1920s and 1930s that developed this method of statistical estimation of the relationship between the inputs and output of a firm. One example is Bronfenbrenner and Douglas (1939). Subsequently several studies such as Motohashi (2001) have used this empirical strategy to study the productivity of a firm.

The basic form of this function is as follows:

$$Y = AK^{\alpha}L^{\beta}$$

The output of a productive unit depends on the inputs—capital, denoted by K, and labour denoted by L. The parameters α and β are the output elasticities of capital and labour. When the sum of α and β is equal to one or greater than one, a firm is said to have a constant or increasing returns to scale, respectively.

A log linear version of the Cobb–Douglas Production function is used to formulate the following estimation equation:

$$ln\_gva_{ij} = c + \alpha\ (ln\_gfa)_{ij} + \beta\ (ln\_\text{emptmandays})_{ij} + \varepsilon_{ij} \quad (1)$$

Where, *ln_gva* is the log of the gross value added of a firm, that is, the value of the outputs less the value of intermediate goods used in the production process. Capital is indicated by the log of gross fixed assets (*ln_gfa*). The variable *ln_totempt_mndays* refers to the total amount of labour employment in a firm measured in terms of man-days. The subscript i refers to the firm and j indicates the 5-digit NIC code pertaining to the firm.

4.2 Extension of the Model to Include Human Capital

Following a long literature that attempted to incorporate human capital as an input into the production process, including Hall and Jones (1999), a similar exercise has been undertaken with this model. The model can be depicted as follows:

$$Y = AK^{\alpha}L^{\beta}(HK)^{\gamma}$$

In the log linear format, this is:

$$ln\_gva_{ij} = c + \alpha\ (ln\_gfa)_{ij} + \beta\ (ln\_\text{emptmandays})_{ij} + \gamma(HK)_j + \varphi_k + \varepsilon_{ij} \quad (2)$$

and

$$ln\_gva_{ijk} = c + \alpha\,(ln\_gfa)_{ijk} + \beta\,(ln\_\text{emptmandays})_{ijk} + \gamma(HK)_{jk} + \varphi_k + \varepsilon_{ij} \quad (3)$$

The term *HK* is measured by using different levels of general education (illiterate, high school education and college education); and of technical education that leads to a degree or a diploma as well as vocational education. These variables are at a level of the 5-digit NIC code. The model represented by Equation (2) undertakes a matching process using only the 5-digit NIC codes. Equation (3) represents the second strategy used for matching the two datasets—via a combination of NIC codes and the state-level location of the firm from ASI data and household from NSSO data. The state-level fixed effects have also been incorporated to account for any idiosyncratic differences that may exist across different states.

5. Results

The results of the baseline model are presented in Table 1 and the ones related to the extended model are presented in the subsequent tables. Certain additional robustness checks are presented in Appendix B.

The baseline estimation of the Cobb–Douglas production function using Equation 1 is presented in Table 1. Columns 1 and 2 used the ASI –2014 and ASI –2012 data, respectively. The results are in alignment with the findings of similar models in the literature. Bronfenbrenner and Douglas (1939) report that various cross-section estimates of the Cobb–Douglas model that use firm-level data from America and Australia find that the coefficient of the log of labour input ranges from 0.65 to 0.75. In general, for most manufacturing firms, nearly three-quarters of the output of a firm can be attributed to labour. This outcome indicates that our baseline regression model is sound enough for us to proceed with further analyses. While Columns 1 and 2 report standard errors clustered at the 5-digit NIC code level, Columns 3 and 4 repeat the analysis with standard errors clustered at the 5-digit NIC code and state levels. The rationale behind doing this is that in the subsequent tables, all the models with the NIC only matching strategy have standard errors clustered at the 5-digit NIC code level. And the models with the NIC plus state matching strategy have standard errors clustered at the 5-digit NIC code and state levels.

Tables 2 to 7 extend the baseline model to include various combinations of indicators of educational attainments. Table 2 explores the role of different forms of general education. It is found that the coefficient of higher education is positive and significant, while those of high school and higher secondary school level of education (Classes X and XII, respectively) are not significant. This implies that when the share of workers with higher education in a general stream among the total workers in a particular 5-digit NIC code is higher by, say 0.1, then the productivity of firms would be higher by 2.1 per cent to 5.1 per cent. The contribution of vocational training versus technical education towards firm productivity is depicted in Table 3. If the share of workers with technical education increases by 0.1, then the productivity of firms in that NIC code could be higher by 2.6 per cent to 4.7 per cent over the different specifications of our model. However, the coefficient of vocational education seems to be positive and significant only in the case where 2014 ASI data is matched using the NIC and State strategy.

Table 4 validates these results using a model that includes all levels of general education as well as vocational and technical education. Tables 5 and 6 demonstrate the effect on the gross value added of firms when the Class X (high school) and Class XII (higher secondary school) levels of education, respectively, are analyses in conjunction with vocational and technical education. In both these cases as well, technical education plays a consistently significant role, while vocational training is significant in some of the estimations.

Table 7 compares three alternative options of higher education—general, technical and vocational. In terms of the impact of these different streams of education on the productivity levels of firms, it is found that the coefficients of higher and technical education are positive and significant while those of vocational training are not significant. This indicates that a greater share of workers with vocational training in the workforce of a firm is unlikely to have an influence on the production of a firm.

Given that there is a lot of investment in vocational training programmes, these results imply e a cause for concern. Robustness checks in Appendix B (Tables B1 to B4) indicate that vocational training has a positive and significant impact on firm productivity when the variable is considered individually in a model, but whenever it is combined with other forms of education, it is observed that the significance is lost. The exact reason behind such a phenomenon requires further investigation. This could indicate a lower quality of vocational training in India, and it could also be an outcome of the fact that more productive individuals are likely to opt for general or technical education. As a result, acquisition of vocational training is an option for those who have not managed to enter into the general or technical educational streams.

One additional robustness check is carried out in Table B5, where the gross fixed assets of a firm are broken down into the gross fixed assets of computer equipment and the rest. The first two columns present a baseline model where it can be observed that the gross fixed assets (apart from computer equipment) and the man-days employed have a similar effect on gross value added to the results reported in Table 1. Investment in capital equipment seems to have a much smaller impact on gross value added vis-à-vis other investment and labour inputs. Even in this specification, it is observed that formal technical education remains statistically significant in all models, and the outcome is same for higher education in three out of four models.

On the basis of this evidence, a potential worker of the manufacturing sector may be advised to take up formal technical education. The attainment of higher education in the general and technical disciplines is more effective in this context. This outcome may also inform government policies towards education—a focus on skill development through vocational training rather than formal education may not help in improving the labour productivity of the workers. It is also a cause for concern that school education has a limited impact on the productivity of firms. This may be a sign of the inadequacy of the quality of school education.

6. Conclusion

The goal of this paper was to contribute to the debate on the choice of higher education versus vocational training in India in the sphere of technology education. Two relevant issues about the context of this problem may be noted. First, the technology sector, especially ICT, has contributed immensely to India's economic growth, over the last two decades. Second, India is embarking on a huge skill development mission based on vocational training programmes. Hence, this study is aimed at contributing to the knowledge base that can inform policy decisions on education and training programmes in India in an environment where the growth of firms may be driven by the use of technology.

The levels of productivity of manufacturing firms have been analysed using a Cobb–Douglas production function. Thereafter, the impact of different levels of education on productivity is assessed. It is found that the firms producing products which have a higher share of workers with higher education in a general stream are likely to have higher productivity. This is not surprising, but an unexpected outcome of this study is that firms that have a higher share of workers with school education (secondary or senior secondary levels) have an insignificant effect on the productivity of firms. This could be an indicator of the poor quality of school education in the country.

This study also finds that the share of workers with higher education in a technical field of engineering has a consistent positive and significant effect on the productivity of a firm. However, this is not always true for vocational training programmes in technical fields. This possibly indicates that it may be prudent for individual students to opt for technical education that leads to a degree. This is also a need for policymakers to rethink the focus on vocational training and instead work on improving the efficacy of higher education in the general and technical fields.

However, one should be cautious about throwing the baby with the bath water. The vocational education programme in India could be experiencing a problem of selection bias. If the weakest students consistently select vocational training while the rest have a strong preference for general education, then the vocational education programme will constantly lack quality and dynamism. In such a situation, it would be prudent to focus on encouraging individuals with an aptitude for certain skills to opt for vocational training. There is also a need to ensure a strong level of primary education. Effective skill training starts at the kindergarten stage. Students who have acquired quality primary education would be better prepared to assimilate the training imparted through vocational programmes and would have the pre-requisites to perform better in the programme and to be productive in future jobs.

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TABLES

Table 1: Baseline Model

Dep Var: ln_gva	ASI 2014	ASI 2012	ASI 2014	ASI 2012
ln_gfa	0.324	0.416	0.324	0.416
	(0.019)***	(0.014)***	(0.015)***	(0.010)***
ln_emptmandays	0.788	0.664	0.788	0.664
	(0.026)***	(0.018)***	(0.019)***	(0.014)***
cons	4.227	4.467	4.227	4.467
	(0.265)***	(0.289)***	(0.201)***	(0.222)***
R^2	0.75	0.75	0.75	0.75
N	21,424	18,750	21,424	18,750

* p<0.1; ** p<0.05; *** p<0.01
State fixed effects (coefficients suppressed)
Brackets: NIC 2008 clustered SE in col 1 and 2 and NIC2008*state clustered SE in col 3 and 4

Table 2: General Education

	Matching using NIC		Matching using NIC*State	
Dep Var: ln_gva	**ASI 2014**	**ASI 2012**	**ASI 2014**	**ASI 2012**
ln_gfa	0.323	0.416	0.329	0.428
	(0.019)***	(0.014)***	(0.022)***	(0.014)***
ln_emptmandays	0.789	0.658	0.750	0.628
	(0.026)***	(0.017)***	(0.027)***	(0.017)***
highschool_nic_sh	0.124	0.079	0.050	0.070
	(0.133)	(0.133)	(0.064)	(0.075)
highsecschool_nic_sh	0.196	0.184	0.003	-0.028
	(0.146)	(0.146)	(0.083)	(0.084)
highered_nic_sh	0.319	0.512	0.212	0.224
	(0.117)***	(0.151)***	(0.067)***	(0.078)***
_cons	4.099	4.353	4.301	4.254
	(0.258)***	(0.274)***	(0.293)***	(0.278)***
R^2	0.75	0.76	0.75	0.76
N	20,145	17,776	11,073	10,718

* p<0.1; ** p<0.05; *** p<0.01
State fixed effects (coefficients suppressed)
Brackets: NIC 2008 clustered SE in col 1 and 2 and NIC2008*state clustered SE in col 3 and 4

Table 3: Technical vs Vocational Education

Dep Var ln_gva	2014/nic	2012/nic	2014/nic*state	2012/nic*state
ln_gfa	0.322	0.418	0.327	0.426
	(0.019)***	(0.014)***	(0.022)***	(0.014)***
ln_emptmandays	0.791	0.658	0.753	0.632
	(0.026)***	(0.017)***	(0.027)***	(0.017)***
voc_tech_nic_sh	0.249	0.427	0.186	0.155
	(0.234)	(0.259)	(0.105)*	(0.101)
techedu_nic_sh	0.368	0.477	0.292	0.264
	(0.153)**	(0.171)***	(0.080)***	(0.086)***
_cons	4.180	4.454	4.321	4.262
	(0.271)***	(0.293)***	(0.298)***	(0.285)***
R^2	0.75	0.76	0.75	0.76
N	20,145	17,776	11,073	10,718

* p<0.1; ** p<0.05; *** p<0.01

State fixed effects (coefficients suppressed)

Brackets: NIC 2008 clustered SE in col 1 and 2 and NIC2008*state clustered SE in col 3 and 4

Table 4: General, Technical and Vocational Education

Dep Var: ln_gva	2014/nic	2012/nic	2014/nic*state	2012/nic*state
ln_gfa	0.321	0.414	0.327	0.424
	(0.019)***	(0.014)***	(0.022)***	(0.014)***
ln_emptmandays	0.790	0.658	0.752	0.631
	(0.026)***	(0.017)***	(0.027)***	(0.017)***
highschool_nic_sh	0.144	0.105	0.103	0.115
	(0.132)	(0.132)	(0.067)	(0.079)
highsecschool_nic_sh	0.218	0.198	0.050	0.016
	(0.143)	(0.147)	(0.083)	(0.087)
highered_nic_sh	0.257	0.428	0.197	0.209
	(0.119)**	(0.150)***	(0.065)***	(0.074)***
voc_tech_nic_sh	0.137	0.209	0.136	0.086
	(0.245)	(0.272)	(0.105)	(0.100)
techedu_nic_sh	0.322	0.363	0.294	0.265
	(0.134)**	(0.147)**	(0.082)***	(0.092)***
_cons	4.089	4.357	4.300	4.257
	(0.257)***	(0.273)***	(0.291)***	(0.275)***
R^2	0.75	0.76	0.75	0.76
N	20,145	17,776	11,073	10,718

* p<0.1; ** p<0.05; *** p<0.01

State fixed effects (coefficients suppressed)

Brackets: NIC 2008 clustered SE in col 1 and 2 and NIC2008*state clustered SE in col 3 and 4

Table 5: Class X, Vocational and Technical Education

	2014/nic	2012/nic	2014/nic*state	2012/nic*state
ln_gfa	0.322	0.418	0.327	0.426
	(0.019)***	(0.014)***	(0.022)***	(0.014)***
ln_emptmandays	0.791	0.658	0.753	0.632
	(0.026)***	(0.017)***	(0.027)***	(0.017)***
highschool_nic_sh	0.038	-0.042	0.031	0.043
	(0.136)	(0.145)	(0.056)	(0.064)
voc_tech_nic_sh	0.253	0.422	0.189	0.159
	(0.233)	(0.257)	(0.105)*	(0.102)
techedu_nic_sh	0.372	0.472	0.299	0.272
	(0.150)**	(0.166)***	(0.083)***	(0.090)***
_cons	4.175	4.459	4.320	4.261
	(0.272)***	(0.297)***	(0.297)***	(0.284)***
R^2	0.75	0.76	0.75	0.76
N	20,145	17,776	11,073	10,718

* p<0.1; ** p<0.05; *** p<0.01
State fixed effects (coefficients suppressed)
Brackets: NIC 2008 clustered SE in col 1 and 2 and NIC2008*state clustered SE in col 3 and 4

Table 6: Class XII, Vocational and Technical Education

	2014/nic	2012/nic	2014/nic*state	2012/nic*state
ln_gfa	0.322	0.417	0.327	0.426
	(0.019)***	(0.014)***	(0.022)***	(0.014)***
ln_emptmandays	0.791	0.658	0.753	0.631
	(0.026)***	(0.017)***	(0.027)***	(0.017)***
highsecschool_nic_sh	0.157	0.109	-0.030	-0.065
	(0.139)	(0.140)	(0.076)	(0.077)
voc_tech_nic_sh	0.257	0.433	0.185	0.154
	(0.234)	(0.260)*	(0.105)*	(0.100)
techedu_nic_sh	0.377	0.480	0.289	0.256
	(0.150)**	(0.170)***	(0.080)***	(0.087)***
_cons	4.159	4.442	4.325	4.268
	(0.268)***	(0.293)***	(0.298)***	(0.287)***
R^2	0.75	0.76	0.75	0.76
N	20,145	17,776	11,073	10,718

* p<0.1; ** p<0.05; *** p<0.01
State fixed effects (coefficients suppressed)
Brackets: NIC 2008 clustered SE in col 1 and 2 and NIC2008*state clustered SE in col 3 and 4

Table 7: General Higher Education vs Vocational and Technical Education

	2014/nic	2012/nic	2014/nic*state	2012/nic*state
ln_gfa	0.322	0.416	0.327	0.425
	(0.019)***	(0.014)***	(0.022)***	(0.013)***
ln_emptmandays	0.791	0.658	0.752	0.631
	(0.026)***	(0.017)***	(0.027)***	(0.017)***
highered_nic_sh	0.218	0.398	0.165	0.178
	(0.119)*	(0.154)**	(0.054)***	(0.061)***
voc_tech_nic_sh	0.130	0.204	0.135	0.087
	(0.244)	(0.270)	(0.105)	(0.100)
techedu_nic_sh	0.305	0.353	0.270	0.243
	(0.139)**	(0.149)**	(0.077)***	(0.084)***
_cons	4.144	4.396	4.313	4.261
	(0.262)***	(0.275)***	(0.295)***	(0.279)***
R^2	0.75	0.76	0.75	0.76
N	20,145	17,776	11,073	10,718

* p<0.1; ** p<0.05; *** p<0.01

State fixed effects (coefficients suppressed)

Brackets: NIC 2008 clustered SE in col 1 and 2 and NIC2008*state clustered SE in col 3 and 4

APPENDIX A

Definitions of variables used in the regression analysis:

- gva = gross value added of firm (output – domestic input – foreign input)
- gfa = gross fixed assets of firm (capital)
- emptmandays = total employment of the firm in terms of man-days (labour)
- highschool_nic_sh = no. of individuals who have attained secondary school education (class X) over the total number of individuals employed in a particular NIC code (and NIC code and state in the case where matching process includes state) in the entire country based on the NSSO data.
- highsecschool_nic_sh = no. of individuals who have attained higher secondary school education (class XII) over the total number of individuals employed in a particular NIC code (and NIC code and state in the case where matching process includes state) in the entire country based on the NSSO data.
- highered_nic_sh = no. of individuals who have attained graduate, postgraduate and above level of education in a general (or non-technical) field over the total number of individuals employed in a particular NIC code (and NIC code and state in the case where matching process includes state) in the entire country based on the NSSO data.
- voc_tech_nic_sh = no. of vocational training recipients in the field of electrical, electronic and computer sciences over the total number of individuals employed in a particular NIC code (and NIC code and state in the case where matching process includes state) in the entire country based on the NSSO data.
- techedu_nic_sh = no. of individuals who have attained technical education field of engineering/technology at any level (undergraduate, postgraduate etc.) over the total number of individuals employed in a particular NIC code (and NIC code and state in the case where matching process includes state) in the entire country based on the NSSO data.
- gfa_ce = gross fixed assets of computer equipment
- gfa_nonce = gross fixed assets apart from computer equipment

APPENDIX B: Robustness Checks

Table B1: ASI 2014 – NSSO 2012 Matched Using NIC Code

Dep Var ln_gva	1	2	3	4	5
ln_gfa	0.324	0.324	0.323	0.323	0.323
	(0.019)***	(0.019)***	(0.019)***	(0.019)***	(0.019)***
ln_emptmandays	0.789	0.789	0.789	0.790	0.791
	(0.027)***	(0.027)***	(0.026)***	(0.027)***	(0.026)***
highschool_nic_sh	-0.014				
	(0.141)				
highsecschool_nic_sh		0.115			
		(0.141)			
highered_nic_sh			0.282		
			(0.118)**		
voc_tech_nic_sh				0.426	
				(0.222)*	
techedu_nic_sh					0.413
					(0.153)***
_cons	4.198	4.181	4.148	4.202	4.174
	(0.276)***	(0.272)***	(0.262)***	(0.274)***	(0.271)***
R^2	0.75	0.75	0.75	0.75	0.75
N	20,145	20,145	20,145	20,145	20,145

* p<0.1; ** p<0.05; *** p<0.01
State fixed effects (coefficients suppressed)
Nic2008 clustered SE

Table B2: ASI 2012 – NSSO 2012 Matched Using NIC Code

Dep Var ln_gva	1	2	3	4	5
ln_gfa	0.422	0.421	0.417	0.419	0.419
	(0.014)***	(0.014)***	(0.014)***	(0.014)***	(0.014)***
ln_emptmandays	0.657	0.656	0.657	0.657	0.657
	(0.018)***	(0.018)***	(0.017)***	(0.018)***	(0.017)***
highschool_nic_sh	-0.121				
	(0.155)				
highsecschool_nic_sh		0.066			
		(0.140)			
highered_nic_sh			0.485		
			(0.157)***		
voc_tech_nic_sh				0.673	
				(0.258)***	
techedu_nic_sh					0.562
					(0.180)***
_cons	4.470	4.449	4.387	4.468	4.446
	(0.304)***	(0.299)***	(0.275)***	(0.298)***	(0.293)***
R^2	0.75	0.75	0.76	0.76	0.76
N	17,776	17,776	17,776	17,776	17,776

* p<0.1; ** p<0.05; *** p<0.01
State fixed effects (coefficients suppressed)
Nic2008 clustered SE

Table B3: ASI 2014 – NSSO 2012 Matched Using NIC Code and State

Dep Var ln_gva	1	2	3	4	5
ln_gfa	0.330	0.330	0.329	0.329	0.328
	(0.022)***	(0.023)***	(0.022)***	(0.022)***	(0.022)***
ln_emptmandays	0.751	0.750	0.750	0.751	0.753
	(0.027)***	(0.027)***	(0.027)***	(0.027)***	(0.027)***
highschool_nic_sh	-0.027				
	(0.052)				
highsecschool_nic_sh		-0.073			
		(0.077)			
highered_nic_sh			0.199		
			(0.057)***		
voc_tech_nic_sh				0.277	
				(0.112)**	
techedu_nic_sh					0.316
					(0.081)***
_cons	4.312	4.320	4.304	4.324	4.312
	(0.299)***	(0.299)***	(0.295)***	(0.299)***	(0.298)***
R^2	0.75	0.75	0.75	0.75	0.75
N	11,073	11,073	11,073	11,073	11,073

* p<0.1; ** p<0.05; *** p<0.01
State fixed effects (coefficients suppressed)
Nic2008*state clustered SE

Table B4: ASI 2012 – NSSO 2012 Matched Using NIC Code and State

Dep Var ln_gva	1	2	3	4	5
ln_gfa	0.429	0.430	0.427	0.428	0.426
	(0.014)***	(0.014)***	(0.014)***	(0.014)***	(0.014)***
ln_emptmandays	0.629	0.628	0.629	0.630	0.632
	(0.017)***	(0.017)***	(0.017)***	(0.017)***	(0.017)***
highschool_nic_sh	-0.008				
	(0.059)				
highsecschool_nic _sh		-0.108			
		(0.076)			
highered_nic_sh			0.210		
			(0.064)***		
voc_tech_nic_sh				0.254	
				(0.113)**	
techedu_nic_sh					0.289
					(0.089)***
_cons	4.253	4.263	4.254	4.257	4.259
	(0.286)***	(0.289)***	(0.279)***	(0.286)***	(0.285)***
R^2	0.76	0.76	0.76	0.76	0.76
N	10,718	10,718	10,718	10,718	10,718

* p<0.1; ** p<0.05; *** p<0.01
State fixed effects (coefficients suppressed)
Nic2008*state clustered SE

Table B5: Robustness Check with Gross Fixed Assets of Computer Equipment

	2014	2012	2014/nic	2012/nic	2014/nic*state	2012/nic*state
lngfa_ce	0.096	0.149	0.094	0.139	0.118	0.174
	(0.015)***	(0.020)***	(0.014)***	(0.018)***	(0.012)***	(0.015)***
lngfa_nonce	0.330	0.342	0.329	0.351	0.321	0.344
	(0.018)***	(0.020)***	(0.017)***	(0.020)***	(0.019)***	(0.017)***
ln_emptmandays	0.673	0.574	0.677	0.573	0.629	0.528
	(0.027)***	(0.024)***	(0.026)***	(0.022)***	(0.027)***	(0.020)***
highschool_nic_sh			0.088	0.066	0.073	0.027
			(0.135)	(0.131)	(0.058)	(0.067)
highsecschool_nic_sh			0.138	0.152	0.002	-0.025
			(0.145)	(0.141)	(0.084)	(0.086)
highered_nic_sh			0.166	0.293	0.132	0.129
			(0.106)	(0.126)**	(0.057)**	(0.063)**
voc_tech_nic_sh			0.061	0.187	0.056	0.092
			(0.242)	(0.272)	(0.098)	(0.091)
techedu_nic_sh			0.254	0.261	0.212	0.128
			(0.128)**	(0.133)**	(0.071)***	(0.071)*
_cons	4.164	5.032	4.052	4.881	4.325	4.810
	(0.277)***	(0.324)***	(0.267)***	(0.313)***	(0.277)***	(0.283)***
R^2	0.74	0.74	0.75	0.74	0.75	0.75
N	19,164	16,339	18,019	15,470	9,991	9,308

* p<0.1; ** p<0.05; *** p<0.01
State fixed effects (coefficients suppressed)
Clustered SE