Economics Letters 173 (2018) 30–34

Contents lists available at ScienceDirect

Economics Letters

journal homepage: www.elsevier.com/locate/ecolet

Testing the effect of investments in IT and R&D on labour productivity: New method and evidence for Indian firms

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HIGHLIGHTS

- Do technological investments in IT and R&D contribute to labour productivity growth?
- We test this hypothesis using micro-level manufacturing data from a developing economy.
- The results are robust to transmission bias in production function set up.
- IT and R&D. have a complementary effect on labour productivity.

ARTICLE INFO

Article history:
Received 4 July 2018
Received in revised form 21 August 2018
Accepted 7 September 2018
Available online xxxx

JEL classification:
C33
D24
O3

Keywords:
Information technology
Research & development
Production function estimation
Labour productivity

ABSTRACT

Utilizing a micro-level dataset of 900 firms for the period 2000–2016 from Indian manufacturing, this paper explores the effects of technological investments on labour productivity performance of firms by looking at investments in Information Technology (IT) and Research & Development (R&D). The present study is the first to assess the role of IT and R&D jointly for Indian manufacturing. To control for transmission bias in production function estimation, a GMM-based one step control function estimator is applied. We find large effects of both IT and R&D across various sub-samples. Further, our results imply that there is a complementarity between IT and R&D in generating labour productivity growth.

1. Introduction

Technological advancement is considered to be one of the most crucial factors affecting economic growth. In the growth theories, generation of new knowledge through research and development (R&D) and information technology (IT) leveraged innovations are strongly identified as the major sources of technical progress (Romer, 1990), hence growth.

Empirically, innovative activities, typically proxied by R&D investments, have long been found to boost productivity performance of a firm (Griliches, 1979; Hall et al., 2013). Since the mid-1990s, growth research has also focused on IT as a factor affecting productivity growth (Brynjolfsson and Hitt, 2003; Erumban and Das, 2016). However, a feature of the previous literature is that the role of IT and R&D has been examined singularly, ignoring the possible correlations between the two investments. Given that both IT and R&D are considered as innovational inputs and may be correlated,[1] Brynjolfsson and Hitt (2003) suggest that omitting the role of unmeasured complementary investments may have seriously biased the effect of IT in the previous literature. A few scholars have already highlighted the complementarities between firm's IT capital and intangible, innovational activities such as, R&D, new architecture, new product development and engineering design (see, Corrado et al., 2017). Specifically, evidence on the joint role of IT and R&D has appeared in Hall et al. (2013), Chen et al. (2016) and Cerquera and Klein (2008). A few studies have also assessed whether these assets are complementary or substitutes in the production process, however these have produced a mixed evidence. For instance, Chen et al. (2016) find a complementary effect of IT with respect to R&D effort in 10 European countries. On the other hand, Cerquera and Klein (2008) note that intensive use of IT leads to reduced R&D effort in German firms.

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1 See for example, Hall et al. (2013).

https://doi.org/10.1016/j.econlet.2018.09.003
0165-1765/

Polák (2017) notes that lack of good quality data is a major reason why much of the literature has ignored the possible interplay between these investments. The purpose of this study is to fill this gap. To this effect, we assess the joint effects of technological investments in IT and R&D on labour productivity in a production function framework. This is achieved by analysing micro-level data on Indian manufacturing firms.

Our paper contributes to the literature in the following ways. First, the existing literature examines separately the effects of IT and R&D on labour productivity, which may lead to potentially biased estimates and policy conclusions. We implement a joint framework to assess these investments as well as the related complementarities. Second, most of the studies use traditional estimators to compute production function elasticities which sometimes fail to control for transmission bias or simultaneity associated with input choice. We control for this simultaneity in input choice by employing Wooldridge (2009), a recently developed GMM-based semi-parametric control function estimator. This is the first work employing this method to assess the problem at hand. Lastly, this paper contributes hugely to the growth literature on India by providing evidence on the role of IT in Indian manufacturing firms, which has been a less explored question mainly because of data limitations. To the best of our knowledge, this is also the first attempt to evaluate the effects of IT and R&D jointly for Indian manufacturing. In the relatively new literature on the joint assessment of these investments, the previous literature evidence is available for Italian firms (Hall et al., 2013), Norwegian firms (Rybalka, 2015), European economies (Chen et al., 2016), OECD countries (Pieri et al., 2017).

Broadly, our findings suggest significant effects of IT and R&D on labour productivity in the sample firms. We also find these inputs to be complementary to each other in the production process.

2. Empirical setting

2.1. The labour productivity equation

We assume the following specification for firm i in year t:

$$\ln\left(\frac{Q}{L}\right)_{it} = \ln\omega + \alpha\ln\left(\frac{K_{IT}{}''}{L}\right)_{it} + \beta\ln\left(\frac{K_{O}{}''}{L}\right)_{it} + \delta\ln\left(\frac{K_{RD}{}''}{L}\right)_{it} + \theta\ln(L)_{it} + \varepsilon_{it} \tag{1}$$

where α, β, γ and δ represent the output elasticities of IT capital assets ($K_{IT}{}''$), non-IT/ ordinary capital assets ($K_O{}''$), accumulated R&D capital assets ($K_{RD}{}''$) and labour (L). Q is the firm's output defined in value-added terms. $\theta = \alpha + \beta + \gamma + \delta - 1$ is a measure of scale economies, whereby the values of $\theta > 0, \theta < 0$ or $\theta = 0$ respectively indicate increasing, decreasing and constant returns to scale. $\omega_{i,t}$ is a parameter measuring total factor productivity. It is assumed to evolve as a first-order Markov process:

$$\omega_{i,t} = E(\omega_{i,t}|\omega_{i,t-1}) + u_{i,t} \tag{2}$$

where $u_{i,t}$ is a random shock component assumed to be uncorrelated with the technical efficiency, the state variables in $K_{O_{i,t}}''$ and the lagged free variables $\omega_{i,t-1}$.

2.2. Production function estimation

As per the paradigm of theory of producer behaviour (Berndt and Khaled, 1979), there is a simultaneity between input choice and unobserved productivity shocks (ω) because firms partly determine input quantities based upon prior belief about their productivity. Traditional methods such as Levinsohn and Petrin (2003) deal with this simultaneity in two steps. While these estimators are widely used, the recent production function literature suggests that a major limitation of these methods is that after the first stage of non-parametric conditioning of labour, there is no variation in labour input left for identification of its coefficient (Ackerberg et al., 2007, 2015). Wooldridge (2009) estimator overcomes this limitation by proposing the joint estimation of the two equations under a Generalized Method of Moments (GMM) framework. This framework uses cross-equation correlation to enhance efficiency. Besides, the optimal weighting matrix accounts for serial correlation and heteroscedasticity in the errors (see, online supplement for details).

3. Data

For this paper, we use micro-level data from Prowess database, CMIE. Prowess database is a comprehensive data source capturing commercial activity in India and provides annual financial statements data for a large number of firms. The wide spectrum of firms in the dataset constitute around 70% of the economic activity of the organized industrial sector in India. For the purpose of our study, we clean the data in the following way. First, we drop firms for which data for missing across all years. Secondly, we dropped all entries with obvious data errors such as, a zero or a negative value of assets or expenses. After cleaning the data in this way, our final dataset consisted of an unbalanced panel of 900 firms and spanning 17 years from 2000 to 2016.[2] A detailed description of variables is presented in Table 1.

4. Estimating IT and R&D effects on firm's labour productivity

Table 2 reports the results of production function estimation (Eq. (2)) for the full sample period as well as sub-periods using Wooldridge (2009) estimator.[3]

For each model, we report production function coefficients of labour, IT, non-IT and R&D capital inputs per unit of labour and the number of observations. To test the over-identification restrictions in the GMM estimator, we employ the Hansen instrument-validity test. The null hypothesis of this test is that the instruments are valid and are uncorrelated with the error-term. Results show that the null hypothesis of instrument validity cannot be rejected across the three estimations. For the full sample results, our estimated elasticity with respect to the ordinary capital input is consistent with other studies on Indian manufacturing firms. Sharma (2018), for example, estimates the output elasticity of capital input to be around 0.32 from an OLS estimation of a Cobb–Douglas production function. Our results indicate for positive and statistically significant output elasticities of both IT and R&D capital inputs. This holds true for both the periods. The coefficient of IT for the full sample is 0.04. The implication is that 1 percent increase in IT capital stock would lead to around 0.04 percent increase in labour productivity. Similarly for R&D, the implication is that a unit percent increase in R&D input would lead to around 0.03 percent increase in labour productivity.

2 The Prowess database is based on the National Industrial Classification (NIC) 1998.

3 A more recent method to deal with the identification issue highlighted in Section 2.2 is Ackerberg et al. (2015) (henceforth, ACF). In contrast with Wooldridge (2009), the ACF method assumes an input demand function that is conditional upon the labour input, which allows the ACF estimator the flexibility to accommodate different patterns of inter-temporal adjustment between productivity shocks and inputs. However, the authors of Ackerberg et al. (2015) raise certain caveats regarding the use of this method. For instance, based on simulations, the authors confirm that under situations where the unconditional demand function assumption is valid, the use of ACF correction produces less efficient estimates (see, Ackerberg et al., 2015, pp. 21). In a set of unreported results, we make a similar observation, which restricts us from choosing the ACF method over Wooldridge (2009). We also note that the latter produces unbiased, consistent and efficient results in our set up.