Estimating Returns to Training in the Knowledge Economy: A Firm Level Analysis of Small and Medium Enterprises.

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Abstract

The ongoing digitization of multiple industries has drastically reduced the half-life of skills and capabilities acquired by knowledge workers through formal education. Thus, firms are forced to make significant ongoing investments in training their employees to remain competitive. Existing research has not examined the role of training in improving firm level productivity of knowledge firms. This paper provides an innovative econometric framework to estimate returns to such employee training investments made by firms. We use a panel dataset of small-to-medium sized Indian IT services firms and assess how training enhances human capital, a critical input for such firms, thereby improving firm revenues. We use econometric approaches based on optimization of the firm's profit function to eliminate the endogenous choice of inputs common in production function estimations. We find that increase in training investments is significantly linked to increase in revenue per employee. Further, marginal returns to training are increasing in firm size. Therefore, relatively speaking, large firms benefit more from training. For the median company in our data, we find that a dollar invested in training yields a return of $4.67, and this effect approximately grows 2.5 times for the 75th percentile sized firm. A variety of robustness checks, including the use of Data Envelopment Analysis, are used to establish the veracity of our results.

Keywords: IT services, non-linear growth, ROI of training, productivity, human capital

1. INTRODUCTION

Global sourcing of Information technology (IT) represents a $251.7 billion industry (Gartner Report 2012). The long-term viability of this global industry hinges on the availability of high quality human capital capable of doing complex knowledge work. In an industry where technological change is constant, the quality of human capital is an imperative for sustained growth and a key determinant of the overall firm profitability (Ang et al. 2002).[1] The productivity of human capital in this industry depends significantly upon the technical and other expertise of the employees (Hatakenaka 2008). Yet, globally, highly skilled technical and productive employees are hard to find. For instance, a recent McKinsey study reports that in the US alone there is a shortage of 140,000 to 190,000 people with analytical and managerial expertise and 1.5 million managers and analysts with the skills to understand and make decisions based on the study of big data (Manyika et al. 2011). Thus, growing the quality and quantity of human capital stock for the knowledge economy is a global problem and any strategy that does not take into account the continued development of employee skills and capabilities is short sighted.

Skills shortage and obsolescence in employees have been the bane of IT services companies worldwide (Mourshed et al. 2012, Kochan et al. 2012). Alarmingly, a recent article in NY Times suggests that the gap between what colleges produce and what employers want is widening (Tugend 2013). Colleges do little to equip their graduates with applied knowledge that makes them readily employable in real life projects (Irani 2008, Mourshed et al. 2012, White 2013). These lacunae affect the quality of labor and have a long-term effect on the growth prospects of companies in this industry. Extant literature suggests that one of the primary ways to improve

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[1] Apart from productivity concerns, such growth can result in severe diseconomies of scale, since managing the complexity of large pools of knowledge workers working together to provide end-to-end services is non-trivial (Craine 1973, Brown et al. 1979).

employee productivity is to shore up their technical and managerial skill levels through training (Bapna et al. 2013). Consequently, these firms are observed to not only make initial training investments to fresh college graduates to make them more productive, but also provide continuous training to cope with the dynamic demands of the global clientele and advances in technology (Lee et al. 1995, Tambe and Hitt 2008, Bapna et al. 2013).

Extant research on human capital has examined the returns from these investments in training in the form of wage gains (Slaughter et al. 2007, Mithas and Krishnan 2008, Mithas and Lucas 2010), and productivity improvements (Bapna et al. 2013). However, much of this research has examined returns at the employee level or focused on contexts other than knowledge firms (Ichniowski et al. 1997, Almeida and Carneiro 2009). A pertinent question that then emerges: do these human capital investments improve labor productivity at the firm level, as would be reflected in a firm's production function? There is lack of rigorous research that provides reliable measures of firm-level returns on investments on training for knowledge firms, especially in the context of IT services. We attempt to bridge this gap in the literature by a) positing that the lack of sufficient human capital affects firm productivity, and b) demonstrating, the efficacious role of training in boosting human capital productivity.

To estimate returns on investments (ROI) from training at the firm level, we analyze data from 32 small to mid-sized firms (SME) IT services firms located in India over a period of 3 years. The Indian IT services industry accounts for more than 50% of the global IT services industry (NASSCOM 2012) and has posted double-digit growth rates over the last decade. In India it is well documented that the dearth of employable labor forces these companies to scrape the very bottom of the labor pool in terms of employability and capability – a problem that is acute in

countries where the education system hasn't kept up with the demands of a knowledge-based economy. Thus, the Indian IT services industry provides a rich context for our study.

The top five firms in this sector look for both strategic and societal objectives through their training investments. In contrast, SME firms, which constitute a significant portion of the Indian IT services industry, are looking to improve the productivity of their existing human capital through training. Therefore, the training initiatives of the top five firms are structurally and motivationally different from those of SME firms. Moreover, industry reports suggest that SME firms are increasingly important in providing the next push to the growth of IT services industry (Rebeiro 2010) and hence further motivate us to focus on SME firms for our study.

We find that growth strategies pursued by IT services sector by increasing the number of employees is sub-linear, thereby exhibiting diseconomies of scale. While the popular press reports linear growth and clamors for non-linear growth (Shinde 2009), our results suggest that even linear growth is a fallacious assumption for small and medium IT services companies. More importantly, we find that training investments augment the effectiveness of a firm's human capital, thereby stemming these diseconomies of scale. Furthermore, we show that compared to smaller firms, larger firms benefit disproportionately from their training investments, that is, they realize higher marginal returns from training.

Our study contributes to existing literature on human capital in several ways. Ours is one of the first studies to use a comprehensive econometric framework for analyzing the nature of growth and the concomitant impact of training (Zellner et al. 1966) and adapting it suitably to small panel data sets (Gandhi et al. 2008). This econometric approach is based on optimization of the firm's profit function to eliminate the endogenous choice of inputs common in production function estimations. Further, while prior literature has proposed training positively affects

human capital productivity, the exact impact of training on both human capital productivity and firm level revenues, especially in the context of IT services, firms is not well understood. Our analysis is thus one of the first to provide a glimpse into the impact of training on revenues for IT services firms.

The rest of this paper is organized as follows. Section 2 presents our theoretical framework, where we review the existing literature and describe our econometric model and estimation approach. In Section 3 we describe our data, following which, in Section 4 we present the results of our analysis. Section 5 concludes with directions for future research.

2. THEORETICAL FRAMEWORK

2.1 Literature Review

Our research has its roots in the theory of human capital that has long been argued as a critical resource and a key driver of value for most firms (Becker 1975, Pfeffer 1994). For the global IT services industry, this perspective is even more important as the pool of knowledge workers constitutes both the primary tangible as well as the intangible resource (Hatch and Dyer 2004).

The extant IS literature points to the increased importance of skilled workers in IT industry (Ang et al. 2002), which requires IT workers to master challenging and complex technical and domain related concepts. The added dimension of offshore IT outsourcing amplifies these challenges, where soft-skills and cultural differences play an equally important role (Langer et al. 2008, Levina and Vaast 2008, Joseph et al. 2010). This overall complexity raises the need for significant education inputs either from the education system or from IT services firms themselves.

Extant research has examined the value of training at either the employee or the firm level. In the broader labor economics literature, the returns of human resource management (HRM) practices

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on worker productivity have been previously studied (e.g., Ichniowski et al. 1997). This research underlines the importance of in-house training as one of the most important HRM practices that affect worker productivity. However, most of the earlier work that quantifies returns to training is based on survey data collected from workers, and may suffer from response bias or low response rates (Boyd et al. 1993). More recent work, such as Bapna et al. (2013), uses archival data from a single firm to examine the linkages between different types of human capital investments and employee performance. Controlling for unobservable employee characteristics and possible selection bias, they find significant positive impact of training on employee performance. Their findings suggest that the value of training is conditional upon a focused curricular approach that emphasizes a structured competency development program

Researchers have also analyzed returns to human capital investments at the firm level (e.g. Black and Lynch 1996). While this strand of research investigates the conditions under which employer provided training has more or less effect (Lynch and Black 1995), due to limitations of data or methodology the reported returns on training seemed to be systematically underreported (Bartel 2000). In addition, much of the research on human capital is in the context of non-knowledge sectors such as manufacturing (Almeida and Carneiro 2009). Hence, their generalizability to the context of knowledge workers is unclear, leading to considerable uncertainty regarding the returns to training for firms employing these workers, such as those in the IT services sector. This is the gap in literature that we seek to address.

2.2 Econometric Model

Methodologically, our work relates to the production function estimation literature (Brynjolfsson and Hitt 1996, Lee and Barua 1999, Dewan and Kraemer 2000). Returns from training are typically estimated using a Cobb-Douglas production function (Zellner et al. 1966, Hoch 1958,

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Mundlak and Hoch 1965). However, this approach is likely to suffer from endogeneity of input choice or the simultaneity bias, such that any Ordinary Least Squares (OLS) estimates using these production functions would be biased and/or inconsistent (Beveren 2007). This bias is introduced when the inputs in the production function are not independently chosen but are determined by the unobserved productivity factors of the firm.

To help tackle such econometric concerns, we utilize recent advances in the production function literature (Olley and Pakes 1996, Levinsohn and Petrin 2003, Ackerberg et al. 2006, and Gandhi et al. 2008). We use a variant of the Cobb Douglas functional form, where training is considered to moderate the impact of the labor input (Bartel 1991). We account for endogeneity of inputs based on the optimization approach suggested by Gandhi et al. (2008), as well as the fixed effects models of Wooldridge (2009).

In what follows, we describe our econometric strategy in detail. The output of a firm depends upon both capital and labor. Specifically, the relationship between a firm i's input factors and output, R_{it}, in period t can be represented using a Cobb-Douglas production function as:

$$R_{it} = A_{it}K_{it}^{\delta}L_{it}^{\alpha} \qquad (1)$$

where A_{it} is the firm i's total productivity factor in period t, K_{it} refers to the capital inputs for firm i in period t. The capital can be either intangible or tangible. Note that in the context of knowledge work, intangibles like intellectual property and organizational processes are considered to be highly effective in improving firm productivity. L_{it} captures the human capital input for firm i in period t and is typically operationalized as the size of the labor pool. However, we are interested in estimating not only the effect of human capital but also the impact of training on human capital in improving firm productivity. Hence, to capture the relationship between human capital, size of the labor pool and training investment, we use a variant of the

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Cobb-Douglas production function as suggested by Bartel (1991). We specify $L_{it} = E_{it}(1 + \beta T_{it})$,

where E_{it} is the number of employee in firm i in period t, and T_{it} measures the training that the

firm provides to its employees in that period. This specification of human capital allows us to

capture how employee productivity is enhanced by the factor βT_{it} due to training investments T_{it}.

This accounts for the direct benefits (increase in productivity of the employee due to better

knowledge and skills) and indirect benefits (increase in productivity of employee due to better

support from peers since they too have better skills) of training on employee productivity.

Finally, we define firm level productivity factor A_{it} such that, $\ln(A_{it}) = \delta_0 + \omega_{it} + \varepsilon_{it}$. Here δ_0

refers to the mean efficiency level of all firms over time, ω_{it} represents firm specific productivity

that is observed exclusively by managers before the firm makes its period t input decisions but is

unobserved by the econometrician, and ε_{it} captures unanticipated productivity shocks that the

firm does not observe before making its period t input decisions. ε_{it} includes any measurement

errors as well.

2.2.1 Econometric strategy to identify the β parameter

A key challenge in estimating the parameters of interest from the production function using the

inputs and outputs of profit maximizing firms is endogeneity (Marschak and Andrews 1944).

Endogeneity in such a specification is caused by the presence of production factors that are

unobservable to the econometrician but are observed by the firm management and are thus

transmitted to the firm's optimal choice of inputs. For instance, a firm whose existing

organizational capabilities are synergistic to employee training may find it more attractive to

invest in training. Failure to account for such systematic reasons for training investments would

lead to an upward bias in any estimate of impact of training because the coefficient for training would absorb the positive impact of any such unobserved variables.

We develop an econometric methodology based on Gandhi et al. (2008) to tackle endogeneity in our model. Let the average wage per employee be represented by the parameter W_{it}. Then the profit function for the firm is as follows:

$$\Pi_{it} = R_{it} - W_{it}E_{it} - T_{it}$$

While Gandhi et al. (2008) requires wages provided by each firm to be observable, we do not observe these wages. Gandhi et al. (2008) suggest the use of static variable to resolve this issue.[2] Therefore, in addition to labor, we specify training investment as another static variable to recover another equation based on FOC of the training investment.

In order to identify the coefficients, we note that a firm can maximize its profits in a particular year by choosing all inputs that are flexible enough to be chosen each year (Gandhi et al. 2008). Labor is generally recognized in literature to be a flexible input. We posit that training investment is also such an input because the extent of training investments each year can be considered independent of previous year's investments and can be chosen each year by the management.

Taking the first order conditions of the firm's profit with respect to the firm's decision variables T_{it} and E_{it}, we get:

$$\frac{\partial \Pi_{it}}{\partial E_{it}} = \frac{\alpha R_{it}}{E_{it}} - W_{it} = 0$$

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[2] A static variables is an input variable in which investment can be decided in the short term, hence firm can optimize investment in this factor on an yearly basis

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$$\frac{\partial \Pi_{it}}{\partial T_{it}} = \frac{\alpha \beta R_{it}}{(1 + \beta T_{it})} - 1 = 0$$

Using the above two equations and accounting for the errors committed by the firm in optimization (Maddala and Lahiri 2009), we obtain:

$$R_{it} = \frac{E_{it} W_{it}}{\alpha} + u_{1it} \qquad (2)$$

$$R_{it} = \frac{(1 + \beta T_{it})}{\alpha \beta} + u_{2it} \qquad (3)$$

Here, u_{1it} and u_{2it} represent the error terms arising due to errors in optimization. Equations 2 and 3, however, can still not be estimated as one of these equations requires wage to be an observed variable. Eliminating R_{it} from equations (2) and (3), we get:

$$E_{it} = \frac{1}{\beta W_{it}} + \frac{1}{W_{it}} T_{it} + u_{it}' \qquad (4)$$

In particular, by assuming wages to be invariant across firms and across time, these wages become part of the two coefficients that can be estimated. Equation 4 contains a constant term $(1/\beta W)$, and the coefficient of T_{it} $(1/W)$ in addition to the error term, $u_{it}' (= (u_{2it} - u_{1it})\alpha\beta)$. Notice that the firm's revenue function R_{it}, as shown in equation 1, contained the unobserved firm productivity variable ω_{it} through productivity factor A_{it}, resulting in endogeneity. However, this transformation results in elimination of R_{it} and hence allows us to remove the source of endogeneity in Equation (4). Thus, OLS estimates of Equation (4) would be unbiased.

While we have dealt with endogeneity, one of the two coefficients in equation 4 contains β, and we still have to recover the estimate for β as well as its standard error using the estimates of the

constant and the slope term. We do this by using the Delta method (Oehlert 1992). The delta

method technique can be used for finding the estimates of mean and variance of a nonlinear

combination of estimators (Feiveson 1999). This method is based on Taylor's series expansion to

derive a linear function that approximates the non-linear combination of estimators (Patterson

2010). If we assume that wages are invariant across firms and across time, these wages become

part of the two coefficients that can be estimated. Out of these two coefficients, only one

contains β, whose mean value and variance can be estimated using the delta method. Once we

get the estimators for $1/W$ and $(1/\beta W)$, we apply the delta method to the ratio of $1/W$ and $(1/\beta W)$,

this provides us with an estimate of the mean and variance of β. This information then yields an

estimate of β and also allows us to run a hypothesis test to ascertain whether the estimate of β is

significant.[3]

The challenge with our proposed methodology is that it does not allow us to identify α, the scale

parameter. We discuss this next.

2.2.2 Econometric strategy to identify the *α* parameter

In this section, we discuss our econometric strategy to identify the α parameter, while accounting

for the simultaneity bias. Recall that in addition to the mean efficiency level of firms over time

(δ_0) we specify the productivity factors, A_{it} to be composed of two components (Griliches and

Mairesse 1998) . There is an anticipated part of productivity that is observed by the firm before it

makes its input decisions in a particular period (ω_{it}). Further, there is an unanticipated shock that

is unobserved by the firm and measurement error (ε_{it}). Note that none of the productivity

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[3] Using this method practically is straightforward. The *nlcom* command in STATA (nonlinear combinations of estimators) computes the point estimate, standard errors, test statistics, significance levels and confidence intervals of nonlinear combinations of estimators directly using the Delta method.

components are observed by the econometrician, and hence are subsumed in the total error term $(\omega_{it} + \varepsilon_{it})$.

To recover α, we first take natural logarithms of both sides of Equation (1), yielding:

$$r_{it} = \delta_0 + \delta k_{it} + \alpha l_{it} + \omega_{it} + \varepsilon_{it} \qquad (5)$$

As per convention, we represent the lower case letters to represent the natural logarithms of the variables represented by the upper case letters. Now, if the firm's choice of the input variables depends on ω_{it}, which is unobserved by the econometrician. Hence, these will also be correlated with the total error term $(\omega_{it} + \varepsilon_{it})$. Consequently, the OLS estimators will be biased.

However, our model manifests a panel structure. Therefore, we can utilize panel data techniques to deal with such endogeneity. Specifically, if we assume that the firm level productivity ω_{it} is time invariant, that is, $\omega_{it} = \omega_i$, thus it can be eliminated by differencing in a fixed effects model, taking care of time invariant sources of endogeneity. The equation we estimate is therefore:

$$r_{it} - \bar{r} = \delta(k_{it} - \bar{k}_i) + \alpha(e_{it} - \bar{e}_i) + \alpha\beta(T_{it} - \bar{T}_i) + \varepsilon_{it} \qquad (6)$$

The terms with the bars represent the average of the observations for firm i over all the years in the panel. In the above equation, since we assume $\omega_{it} = \omega_i$, ω_{it} is differenced out in equation 6.

Consequently, the endogeneity problem is accounted for and the estimates are no longer biased. Note that we use the approximation $\ln(1 + \beta T_{it}) = \beta T_{it}$; this approximation is valid if β is small (Bartel 1991).

2.2.3 Further Empirical Checks

We now discuss the final steps in our estimation process. We need to estimate equations (4) and (6) to analyze the effect of training on firm productivity. However, it is possible for the error terms in the two equations to be correlated, and therefore an equation-by-equation regression would be inefficient (Greene 2002). But, as we illustrate, it is unlikely that error terms in Equations (4) and (6) are correlated. The error term in Equation (6) arises from unanticipated productivity shocks and/or errors in measuring the output. Typically, such productivity shocks are unanticipated because they stem from a change in the external environment of the firm. On the other hand, the error term in Equation (4) arises from the inability of the firm to optimize its inputs perfectly. This could be, for example, due to limitations in managerial ability. Thus, theoretically, there is no reason to suspect that the error terms in Equations (4) and (6) might be correlated; we can estimate these equations separately.

Another empirical issue in a system of equations is that of simultaneous equation estimation bias. It is possible that the dependent variable in one of the equations is used as an explanatory variable in other equations; consequently, the system of equations will have endogenous variables. This violates the assumptions of the least squares and results in biased estimates (Greene 2002). Since we are estimating a system of two equations, it may be presumed that we must use the econometric techniques to simultaneously estimate the two equations in order to avoid the estimation bias outlined above.

However, our two equations constitute a recursive system of equations in which there is only a unidirectional dependency among the endogenous variables. Thus, while e_{it} is the endogenous explanatory variable in Equation (6), there is no endogenous explanatory variable in Equation (4). Consequently the two equations can be ordered such that e_{it} is determined only by exogenous variables and r_{it} is determined by e_{it}. In effect, there is no feedback from Equation (6) into

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Equation (4). This rules out any contemporaneous correlation between error term and the explanatory variables. Based on this and the previous arguments, we can separately estimate the two equations using fixed effects regression without any identification problems (Kennedy 2008).

2.2.4 Controls and Robustness Checks

Controls: We now discuss the controls used in our model. Firm revenues may also be impacted by exogenous shocks to the economy that are common to all firms; therefore we include year dummies while estimating Equation (6). Further, while estimating Equation (4), we must account for the fact that the number of employees hired by the firm may depend upon the firm's location. For instance, it is possible that certain locations are constrained in terms of the availability of programmers and firms with offices in such locations may not be able to ramp up its numbers easily. To control for such exogenous location based factors, we divide the country into four groups and create three dummy variables called West, North and East with South being the base group. Since no new offices were opened by firms in the sample during the period 2006-2008, the value of location dummies are time-invariant.

Robustness Checks: We provide two robustness checks for our estimation technique. First, we relax the assumption that errors in Equations (4) and (6) are uncorrelated. We use a Seemingly Unrelated Regression (SUR) to estimate the coefficients.

Second, the fixed effects regression requires us to make an assumption on the invariance of firm productivity across time. We now relax this assumption and consider the firm's anticipated productivity factor (ω_{it}) to comprise of two components: one that is observed and another that is unobserved by the econometrician. Further, recognizing that the observed productivity factor cannot be measured perfectly, firm's anticipated productivity ω_{it} would be

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$$\omega_{it} = \eta \, p_{it} + \lambda_{it},$$

where p_{it} is a variable that is a proxies for the observed firm productivity factor and λ_{it} is the unobserved firm productivity factor. We rewrite the Cobb Douglas production function after taking natural logarithms as:

$$r_{it} = \delta_0 + \delta k_{it} + \alpha l_{it} + \eta \, p_{it} + \omega_{it} + \varepsilon_{it} \qquad (7)$$

Note that extant research establishes Return on Sales as an aggregate measure of productivity of a firm (Banker et al. 1996). We calculate Return on sales (ROS) as the ratio of EBITDA (Earnings before interest, taxes, depreciation and amortization) and Sales. Since the ROS variable changes over time, the assumption about the firm anticipated productivity shock is milder than what is made in a traditional FE approach, as now only the unobserved part of the firm anticipated productivity factor is required to be invariant, but the overall productivity factor can still vary with time. In other words, $\lambda_{it} = \lambda_i$ is a milder assumption compared to $\omega_{it} = \omega_i$ since we capture some impact of the firm specific time variant productivity shocks as part of the observed variables.

We also assess the robustness of our findings by utilizing Data Envelopment Analysis (DEA), an increasingly popular approach used to measure productive efficiency of firms. We elaborate on this approach in section 4.1.

3. DATA

One of the primary challenges in examining the impact of employer funded training is the lack of available data that systematically captures this across the Indian IT services industry. To overcome this challenge, we commissioned the Indian subsidiary of the reputed US based market

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research firm TNS to collect primary data on our behalf.[4] TNS has vast experience in such data collection and used appropriate checks and balances to ensure that the firms were randomly sampled and were representative of the population of interest to us.

Given the challenges in collecting data for our analysis, our initial approach was to cast as wide a net as possible by including as many of the firms in this industry as we could. But we quickly realized that the Indian IT services industry is quite concentrated with the top five firms accounting for roughly 50% of the industry revenues. The vast majority of the remaining firms in this industry deploy training in fundamentally different ways than the top five. The large firms in this industry have made significant long-term strategic investments in training by investing in large training facilities such as the Infosys Corporate University campus in Mysore (Delong 2006). They also participate heavily in the Campus Connect type of programs that represent a backward integration exercise aimed to improve the quality of curriculum in engineering colleges. These societal level investments have a broader objective, that of improving the image of these companies in the eyes of government and society.

In contrast, the smaller IT Services firms direct their training resources directly towards improving the productivity of their existing human capital. Lacking in-house institutionalized facilities for training, these smaller firms rely on external training available in the corporate education market. As a result these large firms face sunk costs of training that other smaller firms in the industry do not.

This fundamental structural difference in the approach to training between large firms and SMEs makes an apples-to-apples comparison difficult. In other words, a dollar spent on training by a smaller firm is not equivalent to a dollar spent by a large firm in this industry. As a result, a

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[4] More details about TNS can be found at http://www.tnsglobal.com/global/alm/india/, accessed Nov 28, 2013.

single sample that includes both large firms and the vast majority of the remaining firms will prove detrimental in deriving robust insights on the impact of training spend. Given that the vast majority of the firms do not make significant long-term investments in building internal training infrastructure, we decided to exclude these 5 large firms and focus our attention on the remaining firms where the training resources are directed primarily towards the existing human capital. In addition to this main rationale, other factors that led to our sample choice decision include:

1) Exclusion of the five largest firms in the IT services industry that together account for 50% of the industry revenues naturally casts our study as analysis of small and medium enterprises (SMEs). The notion and usage of the term SMEs does, to an extent, vary across various reported studies on the IT services industry. The firms in our sample reasonably map to SME categorization in the industry studies that we reviewed (KPMG Report 2008). As these firms are considered increasingly important in providing the next push to the growth of IT services industry (for instance, see Rebeiro 2010), we believe that our focused analysis has a significant practical import, and

2) In the econometric development, we invoke the assumption of wage invariance to extract the key parameters of interest. Inclusion of top five IT services firms in our sample would make the justification of this assumption more challenging as large firms have a resource advantage to attract top talent through significantly more attractive pay packages than the smaller firms.

To gain traction and gather accurate data, we collaborated with TNS to randomly select 81 firms. TNS contacted the head of human resources and the chief financial officers of representative small-to-medium sized IT services firms in India, followed by extensive phone and email interactions. The survey response rate was nearly 40%; no systematic differences vis-à-vis key variables were found between firms that responded and those that did not.

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We collected firm revenues, number of employees, and training investment data annually from 2006-2008 for 32 IT services firms.[5] In particular, the pertinent survey question for training was: "What was the total training expenditure at your firm in the years 2006, 2007 and 2008?"

Where possible, we validated our primary survey data with publically available archival data. In particular, we used the Prowess database maintained by the Centre for Monitoring Indian Economy, an independent economic think-tank headquartered in Mumbai that has been in existence since 1976. Using this database we collected audited information on the firm's intangible assets (inclusive of goodwill, software and others)[6]. In addition, we collected firm revenues, earnings before interest depreciation and taxes, number of employees and training investments whenever available. This helped us validate the primary data collection process, generate return on sales data, and resolve some missing values in the data. Finally, we collected location data through information culled from the firms' websites corporate histories, and office addresses. Tables 1 and 2 provide summary statistics and correlation between key variables. The average firm in our dataset has revenues of $49 million, and an employee base of about 2000; and spends roughly $57 per employee per year on training.

Table 1: Descriptive Statistics

Variables	Number of observations	Mean	Standard Deviation	Min	Max
Revenue (in million $)	85	49.39107	122.740318	0.2409	856.5045
Employee	84	1942.738	5754.559	53	42017
Training (in '000 of $)	84	111.0048	699.888636	0	6390.909
Intangible assets (in million $)	55	4.777645	8.64406591	0.1	189.37

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[5] The firms in our sample are similar in key variables such as revenue, intangible assets, and number of employees when compared to datasets provided by Standard and Poor's Capital IQ. More details are available upon request from authors.

[6] In the context of an IT services firm, the value added stems from its human capital and its intangible assets. The tangible assets are used primarily to support the human capital. Given the little value add that tangible assets create, coupled with the high correlation with labor in our dataset, we exclude it from our analysis.

Table 2: Correlation Among the Variables

	Revenue	Employee	Training	Intangible Assets
Revenue	1			
Employee	0.9710	1		
Training	0.8487	0.9413	1	
Intangible Assets	0.7192	0.7237	0.4295	1

4. RESULTS AND DISCUSSION

4.1 Analysis and Results

The results of the estimation are reported in Tables 3, 4, and 5 below. Our results also show that the estimates from the fixed effects regression and the SUR approach are very similar. This provides more confidence in our estimates.

We find from estimating equation (6) that α, the coefficient of scale parameter, corresponding to the labor inputs is positive and significant, with a value of 0.583. Note that the coefficient of training investments is $\alpha*\beta$ and not just β.

Table 3: Estimating α[7]

Revenues	Coefficient (Standard Error)		
	FE (without return on sales)	FE (with return on sales)	SUR
Intangible assets	0.2591(0.0688)***	0.2997(0.0657)***	0.2999(0.0611)***
Number of employees	0.4482(0.16110)***	0.5831(0.1376)***	0.5837(0.1281)***
Training investment	0.0002(0.0009)	0.0002(0.0008)	0.0001(0.0007)

---

[7] Year 2 and Year 3 are the year dummy variables and refer to the second and the third year in the panel.

Year 2	0.0542(0.0489)	0.0248(0.0427)	0.0249(0.0397)
Year 3	0.1281(0.0701)*	0.0781(0.0620)	0.0782(0.0577)
Return on sales		-0.1055 (0.0721)	-0.1060(0.0671)
R^2	0.53	0.66	0.66

*$p<0.10$; **$p<0.05$; ***$p<0.01$

Likewise, from estimating Equation (4) using a pooled OLS we find that coefficient of the training input β is also positive and significant with a value of 0.0056. Note that the estimate and standard error of β was recovered using the delta method from the estimates provided in Table 4. Our pooled OLS approach requires the standard assumption of perfect competition amongst firms in the labor market where any wage differentials are competed away. In addition, the short three-year window allows us to assume wage invariance.

Table 4: Estimating β

No. of employees	Coefficient (Standard Error)	
	Pooled OLS	SUR
Training investment	4.9210(0.2077)***	5.029(0.1982)***
East	103.9684(400.729)	-1161.313(481.0014)**
North	326.223(313.2806)	558.4391(408.9191)
West	199.4337(296.6804)	161.2108(386.8908)
R^2	0.89	0.94

*$p<0.10$; **$p<0.05$; ***$p<0.01$

We conducted additional analysis to assess the robustness of the findings by utilizing an alternate measurement specification of the observed productive efficiency of the firm. This is an important source of the endogeneity that dictates input choices made by the firm. In the main analysis reported thus far we utilized return on sales as a measure of the firm's productivity. Return on

sales is an accounting based measure and can potentially be a misleading indicator of a firm's productive efficiency. Further, one can argue that return on sales, constructed from financial information, is far removed from a production function formulation that characterizes the transformation of productive inputs to desired firm outputs. To address this concern, we utilize the Data Envelopment Analysis (DEA) to develop and analyze firm productivity.

DEA is a non-parametric approach to evaluate relative efficiency of productive units operating under the same unspecified technology that defines production possibilities. While the conceptual roots of DEA are similar to economic production functions, an advantage of DEA is that it utilizes the actual data to derive the 'efficiency frontier' against which each productive unit is assessed. Consequently, no explicit functional form of the production function needs to be specified. The efficiency frontier is generated by a mathematical programming algorithm and is used compute the productive efficiency of each unit. We employ the algorithm developed by Banker, Charnes, and Cooper (1984) that allows for varying returns to scale for generating the DEA variable. These computed DEA efficiency scores are used as a measure of observed firm productivity factor. Then we estimate α by replacing ROS by DEA variable. The results are reported in Table 5.

Table 5: Estimating α using DEA Computed Efficiency

Revenues	Coefficient (Standard Error)	
	FE	SUR
Intangible assets	0.3367(0.0715)***	0.3367(0.0658)***
Number of employees	0.5696(0.1266)***	0.5697(0.1164)***
Training investment	-0.0002(0.0008)	-0.0003(0.0007)
Year 2	0.0050(0.0429)	0.005(0.0395)
Year 3	0.0315(0.0620)	0.0315(0.0571)

Revenues	Coefficient (Standard Error)	
	FE	SUR
DEA	0.0247(0.0112)**	0.0247(0.0103)**
R^2	0.74	0.74

*p<0.10; **p<0.05; ***p<0.01

The directional and qualitative similarity of results of the estimation results reported in Tables 3 and 5 underscores the robustness of our findings.

It is also useful to discuss the coefficients corresponding to the control variables. We find that intangible assets are significant. Like in previous works on IT productivity, we use year dummies to control for the exogenous economy specific shocks that are common to all firms. Such shocks will have an impact on productivity of firms and so we must isolate their impact from the impact of the factors of production. However, the coefficients of the year dummies are insignificant at the 5% level suggesting that the macroeconomic factors do not play a significant role in our setting. The coefficients for all the location controls are mostly insignificant which shows that location may not be a significant driver of a firm's number of employees. This points out that if certain locations may have a better and bigger employee pool available, these locations may have larger numbers of potential employers and so there is no significant advantage or disadvantage of location as far as hiring is concerned.

4.2 Limitations

To identify the exponents in a production function, Levinson and Petrin (2003, henceforth, LP) suggest an improvement to the method suggested by Olley and Pakes (1996, henceforth, OP). However, the LP approach requires use of additional data in the form of intermediate factors of production that can be adjusted by the firm in the short run. For example, these factors could be

the magnitude of electricity used, or other material inputs. While the econometrician does not observe the productivity shock anticipated by the firm, she can observe the firm's choice of these short term factor inputs. This information is exploited by the LP/OP approach to infer the extent of the productivity shock and hence account for simultaneity bias.

One limitation of our dataset is that we do not have the data for intermediate inputs. Thesedata limitations preclude the use of the OP/LP methodologies directly in our analysis. However, we expect our estimates to be conservative compared to those that may be recovered using the LP/OP approach. This is because the methodology we propose is far less restrictive in terms of the assumptions. This rationale is in line with the findings of Gandhi et al. (2008), where they apply their proposed methodology as well as the LP approach and show the estimates recovered by using their method to be smaller than the estimates obtained through the LP approach. Furthermore, these methodologies assume that the firms' productivity is the only dimension of unobserved heterogeneity across firms. In particular, it is assumed that there are no differences across firms in input/output prices or in technology. In contrast, the estimation approach we outline in section 2 does not require such assumptions. We only assume a competitive labor market where the wages are uniform across firms and time. Since the panel length is short, this assumptions not too extreme.

4.3 Discussion

Our findings provide for a number of practical insights for the management of human capital in knowledge firms, particularly in the IT services industry. Conventional wisdom, as espoused by Indian media, suggests that this industry manifests a linear growth model. In contrast, our results suggest that returns to scale from human resources are significantly sub-linear. Our estimates of α indicate that increasing the labor force increases revenues, however, the revenue per employee

decreases as the firm scales up. We conclude that scaling may involve increased transaction costs of finding qualified employees, increased managerial complexity of making productive use of thousands of knowledge workers, or the effect of scraping the bottom of the barrel recruiting from a lower skilled labor pool.
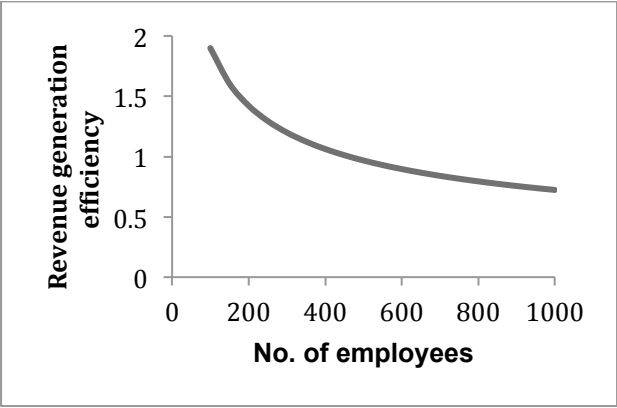

Figure 1: Relative revenue generation efficiency per employee with respect to median firm

Figure 1 compares the revenue generation efficiency of firms of different sizes with a firm of median size. We calculate this as the ratio of revenue per employee across a given firm and the median firm. Ceteris paribus, without training, the revenue generation efficiency decreases as the firm size increases: when the firm is 100 employees, the revenue generation efficiency is 2 times compared to that of the median firm, but when the firm is 1000 employees, this ration is only about 0.75 times that of the median firm as the firm size. As figure 1 shows, scaling reduces the revenue generation efficiency. While initially the smaller firms in the industry may exhibit a near linear growth, as they continue to grow and scale up, they would begin to experience substantial productivity drag. Anticipating this productivity drag is an important first step for these firms to set realistic growth goals and plan their expansion strategy; and our study helps quantify the diseconomies of scale experienced by IT services firms.

More importantly, however, our findings imply that training is very beneficial in enhancing the 'effective labor' and those investments in training yield significant returns. From an investment perspective, how substantial are the returns from training? Dropping subscripts for expositional purposes, the returns to training can be expressed as (from Equation 1):

$$\frac{\partial R}{\partial T} = \frac{\alpha\beta}{(1 + \beta T)}R$$

To derive the magnitude of returns from training, we consider three firms from our sample that differ in terms of size. We chose a firm around the 25th percentile with 200 employees, revenues of $2.89 million and a training budget of $9,000. Similarly, the representative firms around the 50th and 75th percentiles had values of (525, $8.33 million, $150,000) and (1600, $26.7 million, $254,000), respectively. A conservative estimate of the marginal returns (using the lower limit of the 95% confidence interval for β) from each dollar invested in training are:

25th percentile firm: $1.82

50th percentile firm: $4.67

75th percentile firm: $13.91

The above results indicate that the returns from training investments are quite substantial and in line with the returns reported in the literature in other contexts. For example, Bartel 2000 reports training ROI for manufacturing (Hughes Aircraft) and health insurance (CIGNA) to be 3000% and 5900%, respectively.

While the returns from training for a given firm are decreasing, i.e., each additional dollar invested fetches lower returns; the returns from training are increasing with firm revenues. Figure 2 compares revenues per dollar of training for a firm with E employees and training investment T with that of a firm that employs median number of employees and invests at the

median in training (keeping other firm specific variables to be the same). As figure 2 shows, revenues per dollar of training are increasing with increasing scale. Thus, bigger firms have an advantage over small firms in getting benefits from training. Our findings provide compelling rationale for relatively larger firms, which face substantial sub-linearity in growth, to invest their resources in training.
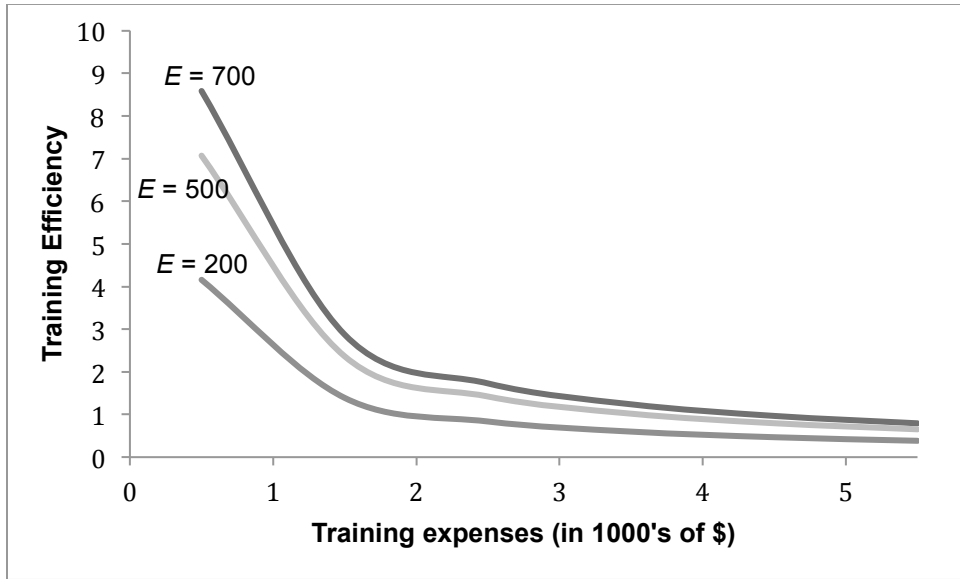

Figure 2: Relative training efficiency with respect to median firm

What is the scope of training investments that firms to maintain linear growth? With some simplification, our estimation reveals that (pulling capital and other terms into the constant term)

$$R = Constant \times \big(E(1 + 0.0056T)\big)^{0.583}$$

The results show that the firm growth is sub-linear with labor (number of employees). However, managers are also interested in analyzing the training investments they should make to realize linear growth, given their current number of employees. To make the above equation linear in the number of employees requires the following.

$$E = \big(E(1 + 0.0056T)\big)^{0.583}$$

Rearranging the terms, we get

$$1 + 0.0056T = E^{\frac{1-0.583}{0.583}}$$

Assuming $\frac{1}{E} \sim 0$, we get

$$\frac{T}{E} = \frac{1}{0.0056E^{0.2852}}$$

Thus, in order to maintain a linear growth model, the training investment needed per employee decreases as the firm scales up. Alternately, it indicates that a given amount of training investment made per employee becomes more effective as the size of the firm grows. These results underscore the importance of training as a key instrument for firms in shaping their growth.

Effective management of human resources entails firms making effective decisions regarding the allocation of their human resources. From the perspective of the overall budget for human resources, our study identifies a fundamental issue: how should firms balance the trade-off between wages and training? Given that the total effective labor is a combination of the number of employees and the human capital generated through training, the allocation decision can be framed as the following optimization problem (as before, for expositional purposes we drop the subscripts).

$$\text{Max } E(1 + \beta T)$$

$$\text{s.t. } \quad T + WE = B$$

Where B is the total budget devoted to human resources. Optimization of the above yields the following:

$$\frac{T^*}{B} = \frac{1}{2}\left(1 - \frac{1}{\beta B}\right)$$

$$\frac{WE^*}{B} = \frac{1}{2}\left(1 + \frac{1}{\beta B}\right)$$

From a budget perspective, 'no more than half, no less than half' is sound normative principle for budget allocation of training and wages. As firms begin to scale up and increase their budget for human resources, they need to devote a larger percentage of the budget for training purposes. Similarly, improved training effectiveness (through innovations in pedagogical approaches and technologies for training) necessitates larger proportion of the human resources dollars directed towards training.

5. CONCLUSIONS AND FUTURE WORK

The global shortage of skilled workers for the knowledge economy has necessitated the need for examining firms' strategies for developing their stock of human capital in on a sustained basis. The rapid pace of technical change in a variety of digitally influenced industries is shortening the half-life of skills and capabilities acquired through traditional university education. Thus, firms are forced to make significant ongoing investments in training their employees to remain competitive. This paper provides a novel econometric framework to estimate returns to such employee training investments made by firms.

We situate our research in the context of the global IT services industry that is particularly vulnerable to skills depreciation. This problem is acute for small and medium sized IT services companies in India (which accounts for 50% of the global IT services industry), which are suffering the consequences of an educational system that has not kept up with the demands of a knowledge economy. While training investments in the Indian IT services industry have been

increasing rapidly,[8] prior research has not examined the linkage between training investments

and firm level revenues for knowledge firms. These SME firms currently occupy nearly 50% of

the overall market and are expected to fuel the future growth of this industry. Unlike the top-five

firms that occupy the other 50% of the market that invest in training from productivity as well as

societal objectives, training investments made by the small-to-medium companies are purely for

increasing employee productivity. Our focus on these firms allows us to identify the effect of

training on firm revenues.

Our work is motivated by the observation that in the absence of credible or unbiased estimates of

returns on training investments (ROI), IT services firms may over or under invest relative to their

optimal level of training investment. Such knowledge is also of prime importance to policy

makers who might be considering allocation of government resources to subsidize private

investments in training. It is also important from the perspective of clients who outsource

knowledge work to the IT services industry. Clients can then make informed decisions about the

reliability and quality of these vendors, affecting their satisfaction with the outsourcing

arrangements. Such client satisfaction in turn has implications for the growth of this industry

(e.g., Langer et al. 2013).

We develop a robust econometric framework based on the recent developments in estimating

production functions with endogenous labor inputs and training investments. We apply this

framework to a unique dataset that captures the training investments made over a three year

period by small-to-medium sized Indian IT services firms. To the best of our knowledge this is

the first attempt at developing a robust methodology for examining returns to training for IT

services firms and our approach is general enough to be applied outside our chosen context.

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[8] For instance, Singh (2010) reports in The Economic Times that the bellwether company Infosys recently increased
their training budgets by 24% over the previous year to a total amount of $230 million for the year 2010-11.

While our work contributes to the human-capital literature by finding the returns to training and analyzing how these returns vary with firm size, this analysis can be extended in several ways. For instance, future research can analyze the impact of training at different levels of the human resource pool, study the relative impact of the different types of training such as soft skill training vis-à-vis project management, and evaluate the impact of training on IT product firms that may have a different business model compared to IT services firms. Future work can also examine the loss of productivity due to "benching" of employees where they do not contribute to revenues and yet are paid their salaries; supply constraints of skilled IT programmers; and managing the complexity of large pools of knowledge workers working together to provide end-to-end services. Finally, different approaches to mitigate these above problems form a rich area for future enquiry.

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