

Digital Transformation and Workforce Productivity: The Role of ICT in Enhancing Labour Productivity

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Abstract

This paper investigates the relationship between investments in Information and Communication Technology (ICT) and labour productivity in 1,071 Indian manufacturing firms from 2000 to 2021. ICT investment is treated as a proxy for technology adoption at the firm level. The analysis reveals a significant effect of ICT expenditure on worker productivity over the past two decades. To capture heterogeneity, the results are further disaggregated by firm size, sector R&D intensity, and manufacturing sub-sectors. The analysis reveals that small firms exhibit relatively greater effects of ICT adoption on labour productivity. Those with medium to high R&D intensity experience significant gains in labour productivity from ICT adoption indicating the role of absorptive capacity of firms in benefiting from such investments. These findings can inform policy decisions for targeted interventions to facilitate the adoption of new and advanced technologies in specific sections of manufacturing firms.

Keywords: ICT investment, technology adoption, labour productivity, Manufacturing sector, India.

JEL Classification: O33, L25, J24, D22, L86, O14

1 Introduction

Manufacturing firms are a fundamental part of India's productive structure, accounting for approximately 17 percent of the organised economic activity employing nearly 28 million people (IBEF, 2025). Despite sustained output growth, manufacturing productivity has persistently lagged behind expectations. Labour productivity in manufacturing declined by 2.8 percent in fiscal year 2022 (Goldar and Aggarwal, 2023). This has raised concerns about India's ability to generate sustained employment growth in the long-run, making firm-level productivity a central policy and research concern. At the same time, during the past decades, there has been a rapid expansion of Information and Communication Technologies (ICT) in both developed and developing countries (World Bank, 2016). The use of ICT capital, such as the internet, computers, and telephone, has become ubiquitous in industries. These developments raise a natural question: to what extent has ICT adoption translated into higher labour productivity in Indian manufacturing firms?

The Solow Paradox (Solow, 1988), which highlighted the disconnect between the ICT adoption taking place in the US during the 1970s and 1980s and the actual productivity gains during this period, generated sustained research interest in the ICT-productivity

nexus. A large empirical literature has since emerged, with mixed findings. A recurring insight is that ICT operates as an enabling technology whose productivity impact depends critically on complementary factors such as firm size, human capital, organisational practices, and R&D investment. However, firm-level evidence for India remains limited, and little is known about how ICT-productivity relationships vary across firms with different absorptive capacities. Understanding this relationship is crucial to assess whether firms genuinely benefit from technology adoption or face transitional frictions due to increased skill requirements. As with general-purpose technologies, productivity gains from ICT may be delayed until complementary skills, organisational changes, and learning processes are in place.¹

Against this backdrop, the present study examines the relationship between ICT expenditure and labour productivity. ICT is defined as firm-level expenditure on communication and information systems that facilitate data transmission, storage, coordination, and decision-making within production processes, including telecommunications infrastructure, internet and broadband services, and software systems. This definition emphasises ICT as an enabling and complementary input to labour in manufacturing firms, highlighting its role in enhancing operational efficiency and productivity.

The analysis is guided by three key objectives. First, we investigate whether ICT expenditure is related with higher labour productivity, a question of growing importance amid the rapid evolution of advanced technologies. Second, we explore the heterogeneity in this relationship across firms through a disaggregated analysis by firm size, and R&D intensity. This provides a lens to understand the differential ability of firms across these dimensions in their ability to absorb and effectively deploy these technologies. Third, a dynamic specification is introduced to capture the persistence in productivity and to explore inter-temporal effects of labour productivity. By focusing on labour productivity and exploiting firm-level longitudinal data, the study provides new evidence on how ICT adoption aligns with productivity performance across heterogeneous manufacturing firms in a developing economy.

From an empirical perspective, this study contributes to the existing literature in several ways. First, our paper provides evidence in the context of a developing economy where the low productivity level of workers has been pointed out as a restricting factor for development and growth. The Indian case is particularly instructive, as the economic transition since the 1990s has facilitated remarkable developments in digital technologies and their influence on firm performance.

Second, unlike most prior research in India that relies heavily on the Annual Survey of Industries (ASI), we use the CMIE Prowess database. This dataset covers key manufacturing industries over the period 2000–2021 and offers greater diversity in both industry coverage and variables, enabling a more detailed analysis.

Third, while earlier studies generally examine overall firm productivity, our study focuses specifically on labour productivity and explores heterogeneity across firm size and R&D intensity. It is reasonable to expect that ICT's effects vary across firms: sectors with limited absorptive capacity, due to lower-skilled labour or fewer complementary resources such as R&D and effective organisational design, may benefit less. These disparities are particularly pronounced in developing countries (Iyer, 2018).

¹Broader literature frequently discusses ICT alongside related technological concepts such as general-purpose technologies (GPTs), automation, and digital transformation. Unlike automation technologies that directly replace or augment physical tasks, ICT primarily facilitates information flows, coordination, and firm efficiency, thereby complementing labour. While these concepts are closely related, ICT in this paper is defined as firm-level expenditure on information and communication services used in production, and the empirical analysis focuses explicitly on this measure.

Finally, while much of the ICT-productivity literature has emphasised industry-level analyses, an emerging stream of micro-level studies highlights positive impacts on firm-level labour productivity (Chen & Lien, 2013; Cirillo et al., 2023). In this context, our study contributes to this literature by examining Indian manufacturing firms over time using longitudinal data.

Drawing on firm-level evidence from a large developing economy, this study contributes to ongoing debates on the productivity effects of ICT and the role of firm heterogeneity in shaping these outcomes. By focusing on labour productivity and accounting for firm heterogeneity and dynamics, the analysis provides new evidence on how digital investment aligns with productivity performance in a developing-country context. The remainder of the paper is organised as follows. Section 2 reviews the related literature, Section 3 provides the conceptual framework, Section 4 describes the data and empirical strategy, Section 5 presents the results and discusses them, and Section 5 concludes.

2 Related Literature

A substantial empirical literature examines the relationship between ICT adoption and productivity. A number of studies support the productivity-enhancing effects of ICT adoption (Greenan and Mairesse, 2000; Maliranta and Rouvinen, 2006; Hwang and Kim, 2022; Maiti and Awasthi, 2020; Laddha et al., 2022; Khanna and Sharma, 2021; Incera et al., 2025), although the mechanisms vary across geographical and industrial contexts. In contrast, a handful of studies report contradictory findings (Haller and Lyons 2015; Colombo et al., 2013).

Increased use of ICT can influence firm performance in multiple ways, including accelerating information flow and product processing, facilitating changes in business operations, and improving internal management and organisational structures. Recent research, particularly for developed countries has increasingly focused on how ICT-driven tools and processes enhance firm performance, rather than just adoption decision. ICT is widely recognised as a technology that streamlines business operations and can lead to productivity gains. Empirical evidence on ICT's impact on output and productivity is mixed, potentially reflecting variations in complementary investments such as training programs and R&D (Fabiani et al., 2005; De and Nagraj, 2014; Sniukiene and Butkus, 2020). Nonetheless, the literature is suggestive that ICT investments not only improves production efficiency but also reshapes the firm's production structures. This interpretation is supported by firm-level evidence from developed economies. Greenan and Mairesse (2000), Brynjolfsson and Hitt (2003), and Hempell (2005) show that ICT adoption significantly enhances productivity in manufacturing and service sectors. Disaggregating ICT investment, Becchetti et al. (2003) find that telecommunications investment supports process improvements and product development, while software investment raises average labour productivity and demand for skilled workers among Italian SMEs. Muller et al. (2018) show that asset accumulation related to big data and analytics increases firm productivity by about 4.1 percent, with stronger effects in more competitive industries. More recent evidence by Hwang and Kim (2022) demonstrates that adoption of advanced digital technologies, including big data, AI, and robotics, increases productivity by approximately 26 percent among Korean manufacturing SMEs.

While ICT can enhance performance, the likelihood and speed of adoption depend on firm-specific characteristics, available resources, and the competitive environment. Several studies have highlighted that factors such as workforce composition, organisational flexibil-

ity, human capital, and firm size play a crucial role in adoption decisions. Fabiani et al. (2005) show that larger firms employing high-skilled labour are more likely to adopt ICT, emphasising the role of white-collar jobs and educated employees in reducing uncertainty and facilitating the diffusion of new technologies. In the Indian context, De and Nagaraj (2014) found that smaller manufacturing firms investing in research and maintaining liquidity often achieve higher productivity gains than larger firms, underscoring the importance of flexible and agile management. These findings are in line with those of Sniukiene and Butkus (2020), who observed that firms in regions with higher ICT literacy and advanced infrastructure are more likely to leverage ICT for productivity improvements. Competitive pressures at both the firm and industry levels can encourage ICT adoption. As Porter (2000) argued, local competition drives innovation and the adoption of new technologies, a conclusion echoed by Fabiani et al. (2005), who note that dense industrial networks and competitive pressures can increase a firm's reliance upon ICT.

Beyond adoption, ICT enhances productivity by reshaping internal management practices and reorganizing production processes. Viollaz (2018) found that Internet adoption in Peruvian micro- and small-scale manufacturing firms promoted formalisation of workers and improved training facilities, leading to higher productivity. Maiti et al. (2020) and Castellacci and Tveito (2018) emphasised that ICT improves efficiency and productivity by enabling better access to information and facilitating effective communication. More broadly, digital transformation contributes to Total Factor Productivity (TFP) through efficient supply chains, enhanced digital innovation, and improved utilisation of human capital (Wu et al., 2025).

At the country level, most studies indicate that ICT investment drives productivity gains in developed economies; however, such evidence for developing countries remains inconclusive (Laddha et al., 2022; Lopez, 2012; Fernandez et al., 2020). In recent years, as developing countries are catching up with developed nations in terms of economic performance, the impact of ICT on driving productivity is undeniable. Several studies have sought to provide valuable insights into the varying economic outcomes of ICT adoption in developing countries. They have identified that inadequate digital infrastructure hampers ICT adoption and limits productivity gains. Commander et al. (2011), using survey data from Brazil and India, underscored the critical role of institutional quality and poor infrastructure in constraining the productivity returns from ICT investment. Their findings highlighted how institutional challenges and pro-labour policies jointly impede the positive effects of ICT. Adhering to this view, Mitra et al. (2011) examined the impact of ICT investment and infrastructure on productivity in the Indian manufacturing sector and found that the effects varied between industries depending on their exposure to foreign competition.

Piatkowski (2003) examines the role of ICT investment in post-communist and transition economies and finds that ICT contributes positively to labour productivity and GDP growth, despite persistent infrastructural and data constraints. A key mechanism identified in this study is the substantial decline in the prices of ICT products and services, which facilitated increased investment in ICT capital. More recent studies shift the focus from investment drivers to the realised productivity effects from adoption of ICT. In this vein, Laddha et al. (2022) show that the adoption of ICT, particularly in telecommunications and broadband, has a positive and statistically significant effect on labour productivity in low- and middle-income countries. However, these gains remain considerably smaller than those observed in high-income economies, indicating that limitations in adoption intensity and supporting infrastructure constrain the productivity-enhancing potential of ICT in developing countries. Khanna and Sharma (2021) provide evidence for India that ICT and R&D investments act as complementary inputs in enhancing productivity in manufacturing firms.

Their analysis reveals that firms investing in both enjoy higher productivity gains compared to firms investing in either of these areas. Investment in innovation is frequently regarded as essential for firm survival and as a means for organisations to distinguish themselves from competitors (Bogetoft et al., 2024). This indicates the complementary nature of technology and R&D investments for productivity growth in the manufacturing sector.

Overall, the literature suggests that ICT investment has the potential to enhance firm productivity, but the magnitude and timing of these effects vary widely across contexts. Evidence points to the importance of complementary factors such as firm size, human capital, organisational practices, and R&D investment in shaping productivity outcomes. For developing economies, and India in particular, firm-level evidence remains limited, with mixed findings across industries and firm types. These gaps motivate a systematic examination of the relationship between ICT and labour productivity in Indian manufacturing firms, with explicit attention to heterogeneity and dynamic effects.

3 Conceptual Framework

Technological know-how and skill level of the workforce play an important role in how effectively inputs are used to produce the intended output. When advanced technology is embedded within these inputs, it can significantly enhance their performance, making the production process more efficient and less resource-intensive. We assume a Cobb-Douglas production function for manufacturing firms with three inputs: capital, labour, and investment in ICT. Investments in ICT include investments in software, hardware, and telecommunications. In this framework, ICT is modelled as a distinct capital input, separate from conventional (non-ICT) capital. That is, ICT represents a form of embodied technological change contributing to enhancing the efficiency and productivity of the factor inputs.

$$Y = AK^\alpha L^\beta ICT^\gamma \quad (1)$$

where, Y is the level of output, K is the non-ICT capital input and L is the labour input. A represents total factor productivity, capturing technology and efficiency, α , β , and γ are the statistically determined parameters. The total factor productivity (A) captures the disembodied nature of technological change. Since it is not directly observed but inferred from the residual component, it identifies the impact of technological diffusion, skill development, and institutional factors concomitant with the adoption of new technology in production. Investment in ICT, on the other hand, accounts for the embodied technological change adopted by the firms as input in production. We hypothesise that investment in ICT enhances labour productivity. Accounting for ICT expenditure enables us to observe the complementarity between technological change and labour input. Advanced technologies are expected to improve the efficiency of the production process. Therefore, achieving the right balance between ICT and other factor inputs is crucial to maximise labour productivity. While ICT is modelled as a distinct input in the production framework, in the empirical analysis it is proxied by firm-level expenditure on ICT-related services, reflecting the intensity of ICT use rather than capital accumulation per se.

The choice of the Cobb-Douglas form of production function offers a number of advantages. One is its simplistic nature. Its log-linear form simplifies estimation and interpretation, especially in panel data settings. Although our chosen production function does not allow for the analysis of input substitution as it assumes the elasticity of substitution between capital and labour to be one, this is not a critical assumption in the context of our

study. Our primary focus in this study is to examine the relationship between investments in ICT and labour productivity.

We derive the equation for labour productivity from the above equation as follows,

$$\frac{Y}{L} = AK^\alpha \frac{L^\beta}{L} ICT^\gamma \quad (2)$$

$$y = AK^\alpha L^{\beta-1} ICT^\gamma \quad (3)$$

where,

$$y = \frac{Y}{L}$$

denotes the labour productivity.

Taking logs on both sides of equation (3),

$$\log y = \log A + \alpha \log K + (\beta - 1) \log L + \gamma \log ICT + \epsilon \quad (4)$$

This yields a linear form of the equation. Equation (4) forms the basis of our empirical strategy. It allows us to identify the relationship between ICT expenditure and labour productivity, controlling for labour input, physical capital, and unobserved firm-level heterogeneity.

It is however recognised that the impact of ICT on labour productivity is likely to be mediated by firm-level capabilities such as R&D intensity, organisational structures, firm size/scale of production as well as sectoral context (Brynjolfsson & Hitt, 2000). In order to account for this, our empirical analysis also includes heterogeneity by firm size and R&D intensity.

4 Data and Methodology

4.1 Data source

We extracted data for 1,071 manufacturing firms from the Prowess database, maintained by the Centre for Monitoring Indian Economy (CMIE). It is a widely used micro-level data source in entrepreneurial research, particularly for studies that analyse firm-level information, including aspects such as ICT adoption, foreign ownership, and productivity in manufacturing firms (Khanna and Sharma, 2024; Mitra et al., 2016; Vashisht, 2018). CMIE collects firm-wise data on ICT expenditure and economic activity of all listed (stock market) companies and a large number of unlisted companies in India. In addition to fundamental economic performance indicators, the CMIE Prowess database offers detailed information on company expenditures on information technology, the import of capital goods, expenditures on R&D and royalties, and more, which makes the database pertinent to our study. The analysis is a comprehensive longitudinal study that spans over two decades, covering the period from 2000 to 2021. Manufacturing firms constitute a substantial portion of the database, providing data on several industries such as textiles, food, chemicals, pharmaceuticals, computers, electrical, and many more. The database assigns each firm a National Industrial Classification (NIC-2008) code corresponding to its primary economic activity. In line with the objectives of this study, we categorise firms using their two-digit NIC codes, dividing the sample into 24 principal manufacturing sub-sectors.

Tables 1 and 2 describe the sample and summarise the variables used in the analysis. Table 1 presents definitions and units for all variables, and while Table 2 reports summary

statistics at the firm–year observation level. The baseline sample includes 1,071 manufacturing firms with a total of 3,855 firm–year observations, although some variables have fewer observations due to missing data.

Table 1: Variable Description

Variable	Description	Unit
Log of Labour Productivity	Log of Labour Productivity	Log (Million Rs. per worker)
Log of ICT expenditure	Log of total expenditure on ICT and its subcomponents	Log (Million Rs.)
Log of Labour	Log of number of employees	Log (Number of employees)
Log of Capital	Log of total (current or non-current) assets held by a company	Log (Million Rs.)
Firm Age	Age of the firm	Years
Log of Import of capital goods	Log of Import of capital goods	Log (Million Rs.)
Foreign dummy	Foreign ownership dummy (1 = Yes, 0 = No)	Binary

Note: Foreign firms are firms with more than 10% foreign ownership or less than 90% Indian ownership

4.2 Variables

In the firm-level empirical literature, labour productivity is a standard observable measure of firm performance (Haltiwanger et al., (1999); Bloom et al., (2012)). This measure is commonly employed in the ICT and productivity literature because it provides a direct assessment of how technology adoption affects labour efficiency, particularly in contexts where detailed input data required for TFP estimation may be limited (Iacovone et al., (2017)). To examine the effect of technology on its complementary input, labour, we use labour productivity as a observed business outcome, which is measured at the firm level by using sales (deflated by the wholesale price index with 2011-12 as the base year) as a proxy for real output and dividing it by the total labour employed. Using sales per worker allows us to capture the channel through which ICT affects the productivity of labour, which is the focus of our analysis. As technological progress is often assessed by its potential to either displace workers or generate renewed demand for skills and labour, understanding the impact of telecommunication technology on manufacturing workers becomes particularly important.

It is important to distinguish between firms that adopt ICT as an input in their production processes and those that produce communication products for sale. Our analysis focuses on the former. ICT, our main independent variable of interest, is the firm’s expenditure on services related to information and communication technology. This includes both basic communication technologies such as telephone, postage, and fax, as well as advanced technologies that facilitate rapid data transmission through satellite services (e.g., VSATs and satellite links), internet services, software systems, IT-enabled services (such as web hosting and co-hosting), and data centres. We aggregate all ICT-related expenses to construct a single variable representing a firm’s overall ICT expenditure, which serves as a proxy for ICT adoption. For some firms, ICT expenditure takes values below one (in millions), resulting in negative values after logarithmic transformation.

To isolate the relationship between ICT expenditure and labour productivity, it is necessary to account for several firm-level characteristics that may influence technology adoption and productivity outcomes. Prior research highlights the role of factors such as worker skill composition, task structure, wage setting, fixed adoption costs, and complementary infrastructure in shaping technology impacts (Acemoglu et al., 2022). Technological adoption may also involve adjustment phases before productivity gains materialise (Helpman and Trajtenberg, 1996). Accordingly, we control for heterogeneous firm characteristics, including firm age, capital and labour inputs, foreign presence, and the use of embodied and disembodied technologies in production. All monetary variables are deflated to 2011–12 constant prices

using the Wholesale Price Index (WPI) published by the Office of the Economic Adviser, Ministry of Commerce and Industry, Government of India.

Table 2: Summary Statistics

	Count	Mean	SD	Min	Max
Firm Age	391,702	19.91	17.39	0	158
Log of Labour Productivity	17,111	-4.29	2.67	-17.19	6.285
Log of Labour	34,685	6.370	1.746	0	12.89
Log of Capital	177,418	5.891	2.40	-2.30	16.08
Log of ICT expenditure	38,352	-0.57	1.62	-2.30	8.94
Log of Import of capital goods	36,493	2.57	2.17	-2.30	11.84
Foreign Dummy	34,470	0.085	0.279	0	1

Note: Summary statistics are authors' calculations based on the overall firm-year data.

Firm's age is measured as the number of years it has been operational, calculated from the year of incorporation to the current year. Firm age reflects the growth process and change in investment and adoption behaviour over time (Coad, Segarra and Teruel, 2016; Fan and Wang, 2021). We also control for the import of capital goods and foreign ownership status. Foreign ownership, defined as a dummy variable, takes the value 1 if the firm has more than 10 percent of its equity shares held by foreign promoters or less than 90 percent of its equity shares held by Indian promoters and 0 otherwise. The term "promoter" denotes an individual or institution that provided the initial equity investment and took on the entrepreneurial initiative to establish the firm. 'Import of capital goods' captures the firm's investment in foreign machinery or equipment. Technological advancement or innovation embodied in such imported capital goods has been recognised as a significant driver of economic growth, a concept often referred to as investment-specific productivity (Greenwood et al., 1997; Cavallo et al., 2018; Caselli and Wilson, 2004). There is a widely held perception, supported by evidence, that advanced economies predominantly engage in innovation and invention activities and are the major exporters of capital goods (Eaton and Kortum, 2001). This implies that technology can be transferred through the trade in capital goods that embody advanced technological know-how. Consequently, it is reasonable to assume that the import of such capital equipment by manufacturing firms in India facilitates significant technology transfer. Hence, we posit that firms in our sample may also experience productivity gains as a result of the increased efficiency derived from these imported capital goods. Both of them combined help us to analyse the factor of foreign dependence of a firm in light of adopting new technology. In the CMIE Prowess database, expenditure on ICT services is recorded separately from investment in machinery and equipment. Therefore, imported capital goods capture embodied technological change through physical capital, while ICT expenditure mainly reflects spending on communication and information services rather than hardware acquisition. Including both variables allows us to distinguish between productivity effects arising from embodied technology in imported capital goods and those associated with ICT-related services.

In order to analyse the heterogeneity across dimensions, such as firm size and firm's R&D intensity, we create subsamples and conduct the analysis for each of these subgroups. For each industry and year, firms are classified into two groups based on median sales: large firms constitute the upper median, while smaller firms form the lower category. Each industry has its own sales distribution per year, making the size variable comparable both across industries and over time. As a result, a firm's classification as small or large is based on its sales relative to other firms in the same industry, as well as in comparison to firms across other sectors. This comparative approach accounts for varying economic scales and industry contexts, ensuring that firms are assessed in a manner that reflects their position

within both their sector and the broader economy (De and Nagaraj, 2014).

Analysing the relationship between R&D intensity and labour productivity can offer meaningful insights into how firms upskill their workforce to complement innovation and technological growth. High R&D intensity and larger firms often go hand in hand, as larger companies typically have the resources to invest in R&D and innovation activities. This is synonymous with global R&D activity being concentrated in a few developed nations, which are consequently experiencing growth due to the adoption of new and advanced technologies (Eaton and Kortum, 2001). Evidence suggests that changes in productivity growth are reflected not only in the unmeasured residuals, as proposed by Solow (1957), but also in improvements in labour quality, skill levels, and capital quality (Griliches and Mairesse, 1995). These factors play a significant role in enhancing efficiency and facilitating technological change in production processes and methods. R&D investments further highlight the potential and interests of producers to adopt high-quality capital. Investment in R&D and changes in productivity growth entail a key relationship that calls for examination. In this context, we analyse how firms’ investment in ICT influences labour productivity in sectors with distinct R&D intensities.

R&D intensity classification follows the OECD taxonomy of economic activities, which is based on the ratio of R&D to value added within an industry (Rueda and Verger, 2016). While the OECD taxonomy uses a fivefold classification (high, medium-high, medium, medium-low, and low R&D intensity industries), we simplify the analysis by creating a threefold grouping: ‘Low’, ‘Medium’, and ‘High’ R&D intensity categories. We map the NIC (National Industrial Classification) codes to the ISIC (International Standard Industrial Classification) codes used in the OECD Taxonomy. It is important to note that both classification systems are largely comparable, as NIC is primarily derived from ISIC Rev. 4. In our study, high- and medium-high industries from the OECD have been ordered together as “High” intensity industries. Similarly, the “Medium” category in our study includes both medium- and medium-high-intensive industries according to the OECD. R&D expenditure serves as a strong indicator of a firm’s technological capacity to innovate, adopt new technologies, and enhance productivity through efficiency gains. Classifying firms by R&D intensity thus provides a robust framework for analysing differences in innovation behaviour and technological adoption. Tracking a firm’s ability to innovate or replicate the innovations of its peers provides valuable insight into productivity growth, especially as ICT serves to complement investments in innovation and invention (Brynjolfsson and Hitt, 2000).

4.3 Econometric Specification

To estimate this relationship between labour productivity of a firm and investments in ICT, we use the following specification, derived from equation (4), as the baseline model of our analysis

$$Y_{it} = \alpha_0 + \beta_0 ICT_{it} + \gamma' X_{it} + \lambda_t + \lambda_i + \varepsilon_{it} \quad (5)$$

The dependent variable is the log of labour productivity of the firm i in year t . The primary coefficient of interest β_0 quantifies the relationship between labour productivity and ICT_{it} , which represents the log of firm’s expenditure on ICT during the year t . To account for other factors that can influence productivity, the model includes a vector of control variables X_{it} such as the logarithm of labour employment that captures the scale of the workforce, the logarithm of total assets serving as physical capital, the age of the firm and the size of the firm reflecting life cycle and scale effects, the ownership status of the firm, foreign exchange spending on import of capital goods by firms, and γ' is the vector of

associated coefficient. By incorporating these controls, the model aims to isolate the effect of ICT expenditure on labour productivity, ensuring robustness in the estimated coefficient. However, the study faces limitations in including additional control variables due to the unavailability of rich data on several potential determinants.

To account for the unobserved heterogeneity in the model, we employ a static panel data estimation approach and then proceed to a dynamic framework. Since our data set is a micro panel with a large number of firms ($N = 1,071$) and a relatively short time dimension ($T = 22$), unobserved firm-specific effects are more likely to be correlated with explanatory variables. The Hausman specification test (Hausman, 1978) formally confirms this by rejecting the null hypothesis of no correlation, thus favouring a fixed effects model over random effects. In the fixed effects (FE) model, each firm has unobserved individual-specific effects, which capture all time-invariant characteristics of that firm. Fixed-effects estimation allows these individual effects to be correlated with the regressors in the model. The unobserved effects are differenced out by using within-effects over time, isolating the effect of variables that do change over time. The FE model examines unobserved heterogeneity by estimating cross-section specific effects λ_i and time effects λ_t . These effects are assumed to be non-stochastic. The panel dataset is unbalanced owing to heterogeneity in firms' years of incorporation.

Further, to take into account the possibility of correlation between labour productivity with its past values and possible endogeneity between ICT expenditure and labour productivity, we also employ a dynamic panel data estimation technique to capture the relationship between ICT expenditure and labour productivity. More specifically, we estimate the following regression equation (6) to capture the dynamic nature of the model, which suggests that the productivity of the worker in the previous period Y_{t-1} might affect the productivity in the current period Y_t , as follows

$$Y_{it} = \alpha_0 + \alpha_1 Y_{it-1} + \beta_0 ICT_{it} + \gamma X_{it} + \lambda_t + \lambda_i + \varepsilon_{it} \quad (6)$$

However, applying fixed effects to equation (6) would give an inconsistent and downward-biased estimate of $\alpha_1 \forall t$, known as the Nickell bias, unless t approaches infinity (Nickell, 1981). The unobserved effects are correlated with the lagged dependent variable, rendering the standard errors inconsistent. To address bias and endogeneity from the lagged dependent variable and unobserved heterogeneity, we use System-Generalised Method of Moments (GMM) with instrumental variables. We difference equation (6) over time to obtain

$$\Delta Y_{it} = \alpha_1 \Delta Y_{it-1} + \beta_0 \Delta ICT_{it} + \gamma \Delta X_{it} + \Delta \lambda_t + \Delta \varepsilon_{it} \quad (7)$$

Where,

$$\begin{aligned} \Delta Y_{it} &= Y_{it} - Y_{it-1} \\ \Delta Y_{it-1} &= Y_{it-1} - Y_{it-2} \\ \Delta ICT_{it} &= ICT_{it} - ICT_{it-1} \\ \Delta X_{it} &= X_{it} - X_{it-1} \\ \Delta \lambda_t &= \lambda_t - \lambda_{t-1} \\ \Delta \varepsilon_{it} &= \varepsilon_{it} - \varepsilon_{it-1} \end{aligned}$$

ΔY_{it-1} and $\Delta \varepsilon_{it}$ are correlated by construction, which makes it necessary to use instrumental variables. The system-GMM approach (Arellano and Bover, 1995; Blundell and Bond, 1998), allows us to choose suitable lagged levels of the variables and combine them with their first differences. It also includes level equations where lagged first differences

serve as instruments for $Y_{i,t-1}$ and $ICT_{i,t}$. Thus, the two-step estimator takes into account all possible orthogonality conditions and any weak instrument or instrument proliferation problem by considering suitable lagged levels of the first difference variables as instruments. To eliminate dynamic panel bias, we utilise the forward orthogonal deviation method in lieu of first-difference transformation to enable minimum data loss and render lagged observations valid as instruments. It subtracts the average of all future observations from the current observation, rather than the previous observation from the contemporaneous one. We check for consistency of system GMM estimates under two parameters: the Sargan/Hansen tests of over-identifying assumptions, which examine the exogeneity condition between the instruments and error terms; Arellano-Bond tests for AR(1) and AR(2) for testing the serial correlation.

The other regressors considered may also be endogenous to the model; thus, two-step system-GMM allows for lagged endogenous regressors to be included as the set of explanatory variables. Roodman (2009) advocated using minimum number of instruments, the standard being fewer than the individuals. We also use the Windmeijer correction method for small sample corrections in the variance-covariance matrix. In small samples, this adjustment corrects for the calculated asymptotic standard errors, which are otherwise downwardly biased (Windmeijer, 2005).

5 Results and Discussions

5.1 Baseline relationship between ICT expenditure and labour productivity

We estimate our baseline equation (5) and subsequent equation (6) for the full sample with different specifications. These are presented in Table 3. Column 1 displays pooled OLS estimates, columns 2–4 provide fixed effects estimates, and column 5 displays the two-step system-GMM estimates.

Pooled estimates show a positive and significant impact of ICT on the labour productivity of manufacturing firms. However, considering that a pooled regression model does not capture the unobserved heterogeneity, a fixed-effects model is fit to deal with the unobserved heterogeneity across both cross-section units and time periods. In column 3, we introduce key control variables along with firm fixed effects. With firm fixed-effects, we are effectively restoring homogeneity across i but not t . Column 4 further refines the model by adding both firm and time fixed effects. Subsequently, we incorporate two additional control variables in columns 4 and 5. However, these two variables are observed for a relatively small subset of observations, which results in a reduction in the sample size. Given the relevance of imported capital goods and foreign-owned firms in shaping labour productivity, we deemed it essential to isolate their effects. Nevertheless, this also serves as a robustness check, as the estimated coefficients remain strongly significant irrespective of a substantial reduction in observations. In the following paragraphs, we first interpret the static panel model and then address the issue of endogeneity with system-GMM estimates.

ICT has a positive and significant impact on labour productivity through all specifications presented in Table 3. Estimates of coefficients for factor inputs, labour and capital, are of expected signs. It can be observed that increasing labour input depresses labour productivity, while higher capital stock is associated with higher labour productivity.

Arrow’s seminal work on endogenous growth theory (Arrow, 1962) proposed that exogenous factors do not singularly govern growth; the accumulation of knowledge over time

Table 3: Regression Results (Full sample)

DV:	(1)	(2)	(3)	(4)	(5)
Log of Labour Productivity	<i>POLS</i>	<i>FE</i>	<i>FE</i>	<i>FE</i>	<i>GMM</i>
Log of ICT Expenditure	0.286*** (0.056)	0.150*** (0.035)	0.084*** (0.017)	0.074*** (0.027)	0.352*** (0.110)
Log of Labour			-0.983*** (0.023)	-0.939*** (0.049)	-1.044*** (0.189)
Log of Capital			0.871*** (0.060)	0.613*** (0.222)	0.688*** (0.143)
Firm Age			-0.033** (0.008)	-0.044*** (0.015)	-0.022** (0.009)
Log of Import of Capital Goods				0.02 (0.015)	0.10 (0.009)
Foreign Dummy				0.348 (0.15)	0.061 (0.305)
Log of Lagged labour productivity					0.212** (0.084)
Time FE				YES	YES
Firm FE		YES	YES	YES	YES
Observations	3855	3855	3855	805	633
R-squared	0.053	0.080	0.645	0.572	
No of Instruments					42
Hansen χ^2 statistic					0.203
AR(1)					0.035
AR(2)					0.367

Robust Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

plays a fundamental role in shaping its growth path. Therefore, the age of the firm is an essential control variable as it reflects the time during which companies have accumulated and incorporated information into their production processes to increase efficiency. Eventually, companies are expected to innovate and adapt to technological advancements. However, as shown in Table 3, the negative and significant coefficients suggest otherwise. This observed structural inertia indicates that, over time, manufacturing firms may become less adaptable to technological adoption and impede labour productivity.

To account for foreign dependence or the impact of imported intermediate goods, we include two additional variables in columns 4 and 5. The adoption of foreign knowledge through the import of technology embedded in capital goods is another form of R&D investment undertaken by the Indian firms. Influence of the type of ownership should also be a determinant in the intensity of acquiring foreign knowledge, thereby impacting efficiency of labour; hence, we use a foreign ownership variable which is binary in nature. Foreign participation in an economy regulates several aspects like technological spillovers with import of technology both in embodied or disembodied forms, or a rise in demand for upskilling of the labour force. However, no significant effect is observed for imported capital goods or foreign ownership.

However, the OLS estimation is likely to be biased due to possibility of endogeneity due to bidirectional relationship between labour productivity and ICT expenditure. More

productive firms may spend more on ICT, while ICT expenditure itself may enhance productivity. In addition, it is possible that past labour productivity affects the current-period productivity, and thus introducing the lagged dependent variable as a regressor to the model is crucial for the analysis. However, including this regressor in an OLS specification could lead to endogeneity. In order to address these issues, we estimate the regression equation (6), adding the predetermined regressor Y_{it-1} , by employing a two-step system-GMM estimation technique. The results are presented in Table 3, column 5. These findings serve as a robustness check for the FE model in column 4, which is presented alongside the GMM estimates. Both models include the same set of control variables, and the dynamic model additionally incorporates the lagged log of labour productivity as a regressor.

The lower panel of the regression table reports the number of instruments used, the Hansen χ^2 statistic for instrument validity, and the Arellano-Bond autocorrelation test statistics, AR (1) and AR (2), for serial correlation in the first-differenced residuals. In addition to using lags of the first-differenced dependent variable, some control variables are also assumed to be endogenous in the model. In the model, ICT expenditure, factor inputs (such as labour and capital), and imported capital goods are treated as endogenous variables, as they are likely influenced by firm-level productivity and strategic decisions. For example, more productive firms may have a greater capacity to invest in ICT or import capital goods, introducing potential reverse causality (Griliches and Mairesse, 1995; Hall, 2011). Foreign ownership and firm age are treated as exogenous. Firm age is determined historically and does not vary in response to current productivity shocks, while foreign ownership is assumed to be influenced more by strategic international investment decisions than by firm-level short-term performance (Aitken and Harrison, 1999; Javorcik, 2004). Our Hansen test statistic confirms the validity of all the instruments used in the model.

In the system GMM estimates, lagged labour productivity does show positive significant impact on current-period labour productivity, suggesting that past productivity does exert a persistent influence on worker efficiency. The coefficient for ICT expenditure increases in magnitude significantly compared to the OLS estimates, with its direction remaining unchanged. Similarly, the coefficients for capital and labour inputs change in magnitude but retain their significance levels. The positive and significant coefficient on log of capital in the GMM estimates further reinforces the role of capital deepening in enhancing labour productivity, consistent with the baseline results. This suggests that increased capital availability enables workers to operate more efficiently, reflecting complementarities between capital and labour. Older firms are associated with lower productivity, while imported capital goods and foreign ownership do not show any significant association with worker productivity. The negative and significant coefficient on firm age persists in the GMM framework, confirming the presence of structural inertia identified earlier. This indicates that older firms may face increasing rigidity and slower technological adaptation over time, which continues to adversely affect labour productivity even after accounting for endogeneity, although the reduced magnitude suggests that the effect is somewhat attenuated once such factors are controlled for.

5.2 Heterogeneity by size

The relationship between firm size and productivity remains an intriguing subject of debate. Theoretically, larger firms, benefiting from economies of scale, are expected to leverage their resources more effectively and achieve significant productivity gains. Contrary to this view, an alternative argument exists which suggests that smaller firms, by streamlining costs, leveraging their risk-taking ability (Scherer, 1998) and operating with less managerial

Table 4: Regression Results by Firm Size

DV:	(1)	(2)	(3)	(4)
Log of Labour Productivity	<i>FE</i>	<i>FE</i>	<i>GMM</i>	<i>GMM</i>
	<i>Small</i>	<i>Large</i>	<i>Small</i>	<i>Large</i>
Log of ICT Expenditure	0.083** (0.033)	0.031 (0.049)	0.210* (0.117)	0.130* (0.175)
Log of Labour	-0.961*** (0.049)	-0.853*** (0.119)	-0.498 (0.221)	-0.520*** (0.149)
Log of Capital	0.471*** (0.139)	0.626*** (0.110)	0.335 (0.285)	0.013 (0.164)
Firm Age	-0.021 (0.023)	-0.029 (0.0196)	-0.024** (0.011)	0.005 (0.002)
Log of Import of Capital Goods	0.025 (0.024)	0.034*** (0.129)	-0.117* (0.062)	-0.003 (0.517)
Foreign Dummy	0.229 (0.132)	-0.004 (0.163)	0.188 (0.217)	0.025*** (0.080)
Log of Lagged labour productivity			0.575*** (0.200)	0.494*** (0.114)
Observations	484	321	369	256
R-squared	0.547	0.730		
No of Instruments			36	80
Hansen χ^2 statistic			0.111	0.054
AR(1)			0.036	0.566
AR(2)			0.563	0.711

Robust Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

complexity (Williamson, 1967), can benefit from increasing returns to scale (De and Nagaraj, 2014).

The literature is ambiguous in deciding on a common metric for the size of a firm. A body of work uses employment as a popular metric for firm size distribution, but most of these studies are based on US and EU (De and Nagaraj, 2014). For our analysis, firm size is defined using sales rather than employment to capture economic scale and to ensure that size classification is independent of labour input, which is included separately in the regression. In Table 4, we estimate the regression equation (5) for two sub-samples characterised by firm size, large and small to examine the relationship between ICT expenditure and productivity. We define a firm to be large if its sales in a year exceed the median sales of the sector in that particular year. Large and small firms are almost evenly represented.

Two sets of model specifications are presented. Columns (1) and (2) correspond to fixed-effects estimates. Labour productivity in small firms is positively and significantly affected by ICT expenditure. However, for large firms we do not see any significant impact in the fixed effects specification. The coefficients for employment and capital are consistent with theoretical expectations of scale effects. Although labour exhibits diminishing returns to scale across both size categories, capital demonstrates positive productivity-enhancing effects. Large firms exhibit insignificant but robust coefficients for firm age in both firm size

Table 5: Regression Results by Firm R&D intensity

DV:	(1)	(2)	(3)	(4)	(5)	(6)
Log of Labour productivity	<i>FE</i>	<i>FE</i>	<i>FE</i>	<i>GMM</i>	<i>GMM</i>	<i>GMM</i>
	Low <i>R&D</i>	Medium <i>R&D</i>	High <i>R&D</i>	Low <i>R&D</i>	Medium <i>R&D</i>	High <i>R&D</i>
Log of ICT Expenditure	0.032 (0.031)	0.124* (0.064)	0.093** (0.041)	0.0859** (0.038)	0.143* (0.076)	0.162* (0.085)
Log of Labour	-1.052*** (0.149)	-1.118*** (0.207)	-0.874*** (0.0612)	-0.845*** (0.266)	-0.0310 (0.136)	-0.749*** (0.149)
Log of Capital	0.465*** (0.162)	0.907*** (0.207)	0.614*** (0.223)	0.459** (0.201)	-0.279*** (0.0947)	0.583*** (0.145)
Firm Age	-0.0354 (0.0266)	-0.0514*** (0.0155)	-0.0185 (0.0245)	-0.00883 (0.0143)	-0.0174** (0.00724)	0.00288 (0.00536)
Log of Import of Capital Goods	0.0202 (0.0177)	0.00692 (0.0239)	0.0394 (0.0242)	-0.0560 (0.0566)	0.0645 (0.0442)	0.136** (0.0649)
Foreign Dummy	0.291** (0.133)		0.301 (0.245)	0.170 (0.428)	0.190 (0.285)	0.0557 (0.162)
Log of Lagged labour productivity				0.481** (0.203)	1.051*** (0.0799)	0.202 (0.141)
Observations	258	219	308	210	175	240
R-squared	0.612	0.776	0.868			
No of Instruments				86	47	41
Hansen χ^2 statistic				0.122	0.862	0.699
AR(1)				0.060	0.065	0.079
AR(2)				0.794	0.626	0.614

Robust Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.010

classifications.

The system GMM estimates in Table 4, columns 3 and 4, yield consistent results with the fixed-effects specifications. Small firms exhibit a robust, positive, and statistically significant response to productivity due to ICT expenditure. The ICT coefficient estimate has increased compared to the FE estimates, however, the level of significance has reduced. Lagged labour productivity also has a strong and positive effect on current-period productivity. The ICT expenditure for large firms indicate significant impact on labour productivity at 10 percent level.

5.3 Heterogeneity by R&D Intensity

Table (5) presents the estimates of Equation (5), with sectors categorised based on their R&D intensity.

We categorise firms into three groups based on their R&D intensity: high, medium, and low. The distribution of R&D intensity is very similar across firm size categories. Among both small and large firms, high R&D-intensive firms constitute the largest share (around 41%), followed by low R&D-intensive firms (approximately 32%) and medium R&D-intensive firms (around 27%).

Columns 1, 2, and 3 present the effects of ICT expenditure on labour productivity across these categories in fixed effects specifications. The coefficient of ICT expenditure is positive and statistically significant at conventional levels across medium and high R&D intensive sectors. Interestingly, medium R&D-intensive firms show the largest productivity gains from ICT adoption, while high-tech firms exhibit comparatively modest improvements. Low R&D-intensive firms exhibit no statistically significant productivity gains from ICT,

suggesting that their production processes, characterized by limited R&D endowments, may require more than basic ICT to enhance labour productivity.

In the dynamic specification in table 5, columns 4-6 for high R&D-intensive firms, the quantum of effect increases with the R&D intensity of the sector. In contrast, low-R&D-intensive firms exhibit lower ICT coefficient, indicating that ICT expenditures may play a more pronounced role in alleviating constraints and enhancing productivity at intermediate and high levels of R&D intensity. Although not explicitly examined in the present study, the results highlight the importance of complementary investments beyond ICT and R&D. In particular, upskilling labour in response to technological innovation may play a crucial role in translating ICT expenditure into productivity gains. In the absence of adequate skill upgrading, investments in new technologies may fail to improve labour productivity, as existing skills become mismatched with more advanced technologies. This underscores the role of human capital as a key complementary factor in realising the productivity benefits of technological change.

6 Conclusion

The Indian economy has followed an unconventional path in its structural transformation, shifting from a predominantly agrarian economy at the time of its independence to a service-dominated economy in recent years. India's manufacturing sector has attained increasing importance owing to the great untapped potential in providing employment to its citizens as well as driving economic growth. With increasing digitalisation and adoption of ICT in production and managerial processes, examining the link between ICT and labour productivity in manufacturing firms is critical. The present study aims to investigate the effect of ICT expenditure on the labour productivity in manufacturing sector firms, in a developing country context of India. From a developmental perspective, this is important due to its implications for firm productivity and broader economic development in a developing country context.

We analyse a sample of 1,071 Indian manufacturing firms during the period 2000 to 2021 to capture this relationship. Sub-samples based on firm size and sector R&D intensity, are further analysed to capture the heterogeneous nature of this relationship. The results of the analysis based on different econometric specifications yield broadly consistent results. We find that small firms experience stronger productivity gains from ICT compared to the larger firms, where the benefits are less pronounced. Further, the productivity effects of ICT expenditure vary across R&D intensity and model specifications. Under the fixed-effects framework, both medium- and high-R&D-intensive firms exhibit significant productivity gains from ICT expenditure. However, once productivity dynamics are accounted for using the system GMM approach, all R&D-intensive sectors display positive and significant ICT effects, with the maximum effects in the High-R&D intensity sectors.

Our findings have important implications for understanding India's manufacturing sector. The positive link between ICT and labour productivity highlights its importance in boosting the competitiveness of the Indian manufacturing sector. The decision to adopt new or sophisticated technologies is typically influenced by an assessment of their potential impact on the production processes of a firm. In India, where the economy is largely driven by labour-intensive industries, the decision to adopt new and advanced technology should comply with the existing skill set of the labour-centric production structure. The results of the study have corroborated the anticipated relationship between advances in technology over time and worker productivity in manufacturing firms. However, the observed variation

in the findings across R&D intensity and firm sizes implies the need for customised policies across different sections of the firms. In conclusion, the evidence indicates that smaller firms and those in the medium and high the R&D intensity sectors are best positioned to harness the benefits of technology adoption. Therefore, policies should aim to make the benefits of technological progress more inclusive for less technology-intensive firms through technological diffusion while strengthening the firms already positioned to adopt and benefit from much advanced technologies. Sectors that are already automated or have high levels of digitalisation are characteristically different from other manufacturing firms that have a low rate of technology adoption. Thus, incentives to adopt technology should be tailored accordingly. They also highlight the importance of aligning ICT adoption with the sector's skill structure and ensuring the availability of complementary factors necessary to realise productivity gains from such adoption.

Intuitively, and as observed empirically, improvements in software technology are positively related to labour productivity. This highlights the importance of exploring the nature of labour demand in terms of skill levels. While our study does not investigate how expenditure in software and telecommunication technology affect the demand for specific skill types, it is evident that complementary hiring and allied investments are crucial for effectively translating technology adoption into technology gains. It will be worthwhile to empirically identify skill types that complement technology adoption or those at risk of substitution due to new technology in Indian manufacturing firms.

Appendix

Table 6: Classification of Manufacturing Activities by R&D Intensity

R&D Intensity	NIC Code	Primary Economic Activity
Low R&D intensity	10	Manufacture of food products
	11	Manufacture of beverages
	12	Manufacture of tobacco products
	13	Manufacture of textiles
	14	Manufacture of wearing apparel
	15	Manufacture of leather and related products
	16	Manufacture of wood and products of wood and cork
	17	Manufacture of paper and paper products
	18	Printing and reproduction of recorded media
	19	Manufacture of coke and refined petroleum products
	31	Manufacture of furniture
Medium R&D intensity	22	Manufacture of rubber and plastics products
	23	Manufacture of other non-metallic mineral products
	24	Manufacture of basic metals
	25	Manufacture of fabricated metal products, except machinery and equipment
	32	Other manufacturing(jewellery, musical instruments, sports goods, games and toys, medical and dental instruments)
High R&D intensity	20	Manufacture of chemicals and chemical products
	21	Manufacture of pharmaceuticals, medicinal chemical and botanical products
	26	Manufacture of computer, electronic and optical products
	27	Manufacture of electrical equipment
	28	Manufacture of machinery and equipment n.e.c.
	29	Manufacture of motor vehicles, trailers and semi-trailers
	30	Manufacture of other transport equipment
	58	Publishing activities

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