Working Paper Series

519

IMPACT OF DIGITALISATION ON FINANCIAL INCLUSION AND FIRM PERFORMANCE OF INFORMAL SECTOR IN INDIA: PRE AND POST COVID ANALYSIS

K. Chandra Shekar
K. Vidyarani

Centre for
Development Studies
Thiruvananthapuram - 695011
Kerala, India

Working Paper

519

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Dr. K. Chandra Shekar

K. Vidyarani

June 2025

CENTRE FOR DEVELOPMENT STUDIES

(Under the aegis of Govt. of Kerala & Indian Council of Social Science Research)

Thiruvananthapuram, Kerala, India

The authors gratefully acknowledge the support received from the OH-31 Research Project, Centre for Development Studies (CDS), and the Indian Council of Social Science Research (ICSSR), which made this study possible. The author is also thankful for the insightful comments and constructive feedback provided by the anonymous reviewers and Prof. P. L. Beena.

Abstract

The informal sector serves as a critical component of economic activity in developing countries. However, enterprises operating within this sector often face considerable obstacles in increasing productivity and achieving financial inclusion. The rapid advancement of digitalisation presents a promising avenue for addressing these barriers and fostering greater financial inclusion and increased productivity in the informal sector. Therefore, this study analyses the impact of digitalisation on firm performance and financial inclusion among informal enterprises in India by considering after and before the COVID outbreak. The study used pseudo panel data constructed using pre and post COVID rounds of the NSSO unincorporated non-agricultural survey (2016 and 2023) and employed a PSM-DID method to ascertain the impact of digitalisation on financial inclusion and firm performance among informal enterprises in India. This study found that the digitalisation significantly enhanced financial inclusion and firm performance immediately after the COVID-19 pandemic. However, the significant effect of digitalisation appears to fade over time and it has been uneven across enterprise types and sectors. This points that the initial gains from adopting digital tools may not be sustained in the long run and highlights the need for targeted interventions to sustain the benefits of digital adoption and ensure long-term productivity gains across different sectors of the informal economy.

Keywords: Informal sector Enterprises in India, Digitalisation, Financial inclusion, Difference in Difference, Propensity score matching

JEL Codes: E26, O17

1 Introduction

Informal sector plays a dominant role in sustaining economic growth and employment in India, particularly in the absence of widespread formal employment opportunities (La Porta and Shleifer, 2014). This suggests the performance and competitiveness of the informal sector play a crucial role in fostering economic growth and improving living standards. The informal sector contributed nearly 45 percent of value added and three-fourth of total non-agricultural employment in 2022 (ASUSE, 2022). However, despite its significance, the sector's contribution to India's Gross Domestic Product (GDP) remains relatively modest and is often perceived as less productive (Krishna et al., 2018; NCEUS, 2009).

Internet penetration has surged from just 0.21 million subscribers in 1999 (MoSPI, 2015) to 969.60 million in 2024 (TRAI, 2024). These advancements highlight the growing role of digitalisation in shaping economic and industrial landscapes. While digital transformation has accelerated growth in the formal sector, the role of digitalisation in the informal sector has become even more critical in the post-COVID period (Bhattacharjee et al., 2024).

Before COVID-19, digitalisation in the informal sector was relatively slow, primarily due to a lack of infrastructure, digital literacy, and financial constraints (Shekar & Mansoor, 2020; Bhattacharjee et al., 2024). The informal economy primarily operated through traditional networks, with limited adoption of digital tools for business transactions, financial services, and supply chain management. However, the pandemic acted as a catalyst, accelerating digital adoption across sectors. Lockdowns and mobility restrictions forced many informal businesses towards digital payment systems, online platforms, and mobile-based financial transactions. Government initiatives such as the Digital India program, along with an increase in digital financial inclusion measures, further facilitated this transition.

While digitalisation has been widely recognised as a General-Purpose Technology (GPT) due to its broad applicability, capacity to drive innovation, and continuous impact across industries (Basu et al., 2003; Biagi, 2013), its effects on informal sector firms have been complex and varied. Theoretical frameworks such as Transaction Cost Economics, the Resource-Based View, and Dynamic Capabilities Theory emphasise ICT's role in reducing operational costs, fostering innovation, and strengthening competitive advantages (Erumban & Das, 2020; Tranos, 2012; Reddy & Sasidharan, 2024). However, empirical findings on digitalisation and firm performance present mixed outcomes. In the pre-COVID period, digital adoption was often limited by inadequate access to credit, low digital literacy, and resistance to change. Some studies suggested that digital investments yielded minimal or even adverse effects due to high adjustment costs, inefficient resource allocation, and the digital divide (Dewan & Kraemer, 2000; Fernández-Portillo et al., 2020; Polák, 2017).

In the phase of digital transformation, financial inclusion[1] has become essential for informal sector enterprises. Although these enterprises face considerable challenges in accessing and utilizing formal financial services, the advantages they can derive from financial institutions are just as significant as those available to formal businesses. Limited access to formal financial systems often compels informal enterprises to depend on personal networks and social relationships to obtain financial resources and manage market inefficiencies. Digital financial services can strengthen these social interactions by improving information sharing, enhancing coordination, and facilitating more frequent engagement with trading partners. This, in turn, helps build trust and lowers transaction costs (Sheikh et al., 2023; Senyo et al., 2023). Additionally, digital financial solutions enable informal enterprises to extend their networks beyond local connections, thereby improving market reach and overall economic performance.

Furthermore, the COVID-19 pandemic had a profound impact on informal sector enterprises, intensifying existing vulnerabilities such as restricted access to financial resources and market disruptions. Lockdowns and travel restrictions significantly reduced sales and created operational challenges, further constraining the sustainability of these enterprises (Shekar & Mansoor, 2020). Adopting digitalisation can help alleviate resource constraints by improving transaction security, enhancing liquidity, and expanding access to external financing. Digital financial services, including mobile money and digital payment systems, have played a crucial role in strengthening the resilience of informal enterprises, particularly during the COVID-19 pandemic. These services facilitate more efficient transaction management, inventory control, record-keeping, and financial planning, thereby fostering greater financial inclusion and enhancing the overall economic performance of informal enterprises. However, despite these advancements, financial inclusion remains a significant challenge for the informal sector, often restricting access to capital and credit.

Post-COVID, the situation evolved significantly. Many small enterprises that adopted digital tools during the crisis experienced improved financial inclusion, expanded market access, and

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[1] *According to (World Bank, 2013), Financial inclusion is defined as the proportion of enterprises access and use of formal financial services.*

greater resilience against economic shocks. However, challenges such as affordability of digital tools, cybersecurity concerns, and lack of digital training persist, hindering the full realisation of digitalisation's benefits. Theories such as the Productivity Paradox, Complementarity Theory, and Mismatch Theory provide explanations for these inconsistencies, highlighting how the absence of complementary investments in workforce training, managerial innovation, and organisational restructuring can lead to suboptimal ICT utilisation (Berndt et al., 1992; Brynjolfsson et al., 2002). Joseph and Abraham (2007), Mitra et al. (2016), Goldar (2020) and Krishna et al., (2020) emphasized on positive effect of digitalisation on Indian manufacturing. While the impact of digitalisation on productivity has been extensively explored in developed economies and formal sector, its evolving effects on informal sector in India require further investigation (Krishna et al., 2018; Polák, 2017; Dewan & Kraemer, 2000).

Against this backdrop, the study provides insights into how digital adoption influences financial inclusion and firm performance in the informal sector pre and post COVID-19 pandemic by utilising nationally representative survey data on unincorporated non-agricultural enterprises in India. The findings suggest that digitalisation significantly enhanced and firm performance immediately after the COVID-19 pandemic. However, the significant effect of digitalisation appears to fade over time and it has been uneven across enterprise types and sectors. These findings of the study provide valuable insights for policymakers, highlighting the need for targeted interventions to sustain the momentum of digital adoption and ensure long-term productivity gains in the informal economy.

The rest of the paper is structured as follows: Section 2 describes the literature. Section 3 provides the data and methodology. Section 4 and 5 contains our main results and discussions based on the empirical analysis. Section 6 provides a conclusion and relevant policy implications.

2 Review of literature

2.1 Informal sector: In Indian context

The Indian labour market is typically classified into the formal and informal sectors. The formal sector consists of legally registered enterprises that adhere to regulatory frameworks, providing employees with structured wages, job security, and standardized working conditions. In contrast, the informal sector encompasses employment arrangements that operate outside legal and institutional regulations, often failing to comply with labour laws and social security provisions. Workers in the informal sector frequently experience job insecurity, irregular incomes, and limited access to social protection measures, making them more susceptible to economic vulnerabilities (NCEUS, 2009). The informal sector is inherently diverse, posing significant challenges for scholars and policymakers in establishing a precise and universally accepted definition of informal enterprises (Mukherjee, 2016). The International Labour Organisation (ILO) and other institutions conceptualize the informal sector as comprising economic activities that exist outside the regulatory and legal frameworks governing the formal economy. These activities are typically characterized by a lack of official recognition, limited access to institutional support, and the absence of social protections, distinguishing them from formally regulated enterprises. Therefore, the informal sector comprises both informal enterprises and informal employment.

The concept of informal enterprises was first formally defined during the 15th International Conference of Labour Statisticians (ICLS), as highlighted by Bhalla (2009). According to the conference, informal enterprises refer to all privately owned, unincorporated, and non-agricultural businesses that are operated by individuals or households and do not function as legally distinct entities separate from their owners. As a result, these enterprises often lack comprehensive accounting records necessary to establish a clear distinction between business activities and the personal financial transactions of their owners. The definition of informal sector enterprises varies across countries and institutions, reflecting diverse conceptual frameworks. Historically, three predominant paradigms have emerged to explain the existence and role of the informal sector: the dualist, structuralist, and legalist paradigms. The dualist perspective characterizes the informal sector as a marginal segment of the economy that exists alongside but remains largely disconnected from the formal sector. In contrast, the structuralist paradigm argues that the informal and formal sectors are interdependent, with the informal sector serving a subordinate function by supplying low-cost labour, inputs, and products to formal enterprises, thereby enhancing economic flexibility and competitiveness. The legalist perspective, however, posits that firms operate informally primarily to circumvent the financial and administrative burdens associated with regulatory compliance (Chen, 2007).

2.2 Digitalisation and Firm Performance: A Critical Review of Theoretical and Empirical Perspectives

2.2.1 *Digitalisation and firm performance*

Digitalisation has profoundly influenced human behaviour, altering the ways individuals communicate, work, and access information. The rapid integration of digital technologies has reshaped everyday activities, including financial transactions, education, and commercial interactions. As digital tools become increasingly embedded in daily life, they continue to redefine social engagement, enhance operational efficiency, and drive innovation across multiple sectors. The expansion of the digital economy is fuelled by advancements in technologies such as the internet, artificial intelligence, and cloud computing, which play a crucial role in shaping industrial development and fostering economic growth (Chen et al., 2022). Additionally, the digital transformation of traditional enterprises has gained momentum, as businesses increasingly adopt digital strategies to remain competitive in an evolving technological landscape. In line with this argument, existing research widely acknowledges that digital transformation can enhance firm performance by reducing operational costs and fostering innovation (Bharadwaj, 2000; Erkmen, 2020; Reddy & Sasidharan, 2024). However, some scholars challenge this view, arguing that digital transformation does not always lead to improved business performance. Curran (2018) posits that there is no direct causal relationship between digital transformation and firm success and suggest that while some enterprises derive substantial advantages from digital adoption, others may not experience the same benefits, highlighting the uneven impact of digital transformation across different firms based on their organizational structures, resources, and adaptability.

Theoretical discussions continue to explore the complexities of the digitalisation paradox (Gebauer et al., 2020) and the productivity paradox (Solow, 1987; Brynjolfsson, 1993). While some studies suggest that only a small proportion of businesses benefit from digital transformation or that there is no clear positive correlation between digitalisation and firm performance (Curran, 2018), others offer a more nuanced perspective. For instance, Guo et al. (2023) argue that while digital transformation can significantly enhance total factor productivity, it may not necessarily translate into improved firm performance. This indicates that the impact of digital transformation on firm performance is not uniformly positive, leading to an ongoing debate regarding its overall effectiveness. There remains a lack of consensus on whether digital transformation consistently enhances business outcomes. Some studies hold that digital transformation can significantly elevate firm performance, whereas others believe that digital transformation has no significant relevance to firm performance (Curran, 2018). In another study, Chen et al. (2022) found that the adoption of traditional digital technologies did not yield a significant improvement in firm performance. These findings suggest that the relationship between digital transformation and firm performance is complex and may depend on various factors such as industry dynamics, technological capabilities, and the strategic implementation of digital initiatives.

Several studies argue that advancements in digital technologies, including the internet and information technology, play a crucial role in enhancing firm performance (Reddy & Sasidharan, 2024). According to Ferreira et al. (2019), digitalisation enables firms to strengthen their competitive advantage, foster innovation, and ultimately improve overall performance. The implementation of digital transformation provides numerous advantages, including enhanced operational efficiency, lower production and sales costs, and the advancement of both technological and managerial innovation. Moreover, the integration of digital technologies facilitates the development of a more structured and efficient production model, ultimately contributing to increased productivity. From an operational perspective, digitalisation not only improves the speed and efficiency of business processes but also enhances a firm's ability to adapt to market dynamics, optimize resource allocation, and strengthen overall business performance (Li et al., 2021; Mithas & Rust, 2016; Reddy & Sasidharan, 2024). Other studies suggest that the implementation of digitalisation often necessitates substantial investments, which may not immediately lead to improvements in firm performance (Yunis et al., 2018). Available research also indicates that the positive impact of digital technologies on firm performance is not always immediate, as there is often a time lag before firms can fully realise the benefits of digital adoption (Bayo-Moriones et al., 2013). This delay underscores the need for long-term strategic planning and continuous adaptation to maximise the potential advantages of digital transformation.

2.2.2 *Digitalisation and Total factor productivity*

Drawing upon the resource-based view (Barney, 2001), the integration of digital technologies within enterprises involves substantial investments in digital resources such as big data and cloud computing. These digital assets not only enhance the value of a firm's resource base but also contribute to greater efficiency in resource allocation. Consequently, this leads to improvements in total factor productivity and strengthens the firm's competitive advantage.

The Resource Based View posits that ICT serves as a strategic resource enabling firms to gain and sustain competitive advantage and thus, drives better performance (Tranos, 2012). Digitalisation generates new marketing methods and electronic markets (Benjamin & Wigand, 1995), facilitating comparative advantages at the firm, regional, and national levels (Tranos, 2012). However, affordability of digital transformation to all enterprises, has hence lost its strategic advantage (Carr, 2003). From an operational standpoint, digital technologies are primarily geared toward efficiency enhancement. Through automation and digitized workflows, firms can optimize resource distribution and maximize efficiency across various functions, including production and business operations. Such comprehensive efficiency improvements not only reduce production costs but also enhance total factor productivity, thereby positively influencing overall firm performance. General Purpose Technology (GPT) Theory explains that digitalisation drive productivity growth when paired with complementary investments in workforce training, organizational changes, and managerial innovation (Bresnahan and Trajtenberg, 1995). The Productivity Paradox and adjustment cost theory suggests that merely investing in digitalisation does not guarantee productivity gains, as firms may face short-term inefficiencies during the adoption phase, including adjustment costs, system integration challenges, and employee resistance (Berndt et al., 1992). Mismatch theory and Complementarity theory suggests that digitalisation favour high-skilled workers, often displacing low-skilled labour and creating challenges for firms lacking a skilled workforce (Sandulli et al., 2014). The J-Curve Effect illustrates the initial productivity decline during digitalisation due to adjustment costs and operational disruptions, followed by long-term gains as firms and employees adapt to digitalisation. Furthermore, digital technologies equip firms with the ability to respond more dynamically to market fluctuations, leverage real-time data analytics for informed decision-making (Karanja & Waiganjo, 2020), and optimize resource utilization, thereby fostering continuous productivity growth. Additionally, digital technologies serve as a catalyst for technological innovation by facilitating disintermediation, which effectively reduces transaction costs (Adamides & Karacapilidis, 2020). Moreover, they promote digital innovation (Nambisan, 2017; Nambisan et al., 2019), further driving total factor productivity and reinforcing the strategic significance of digital transformation in contemporary business environments. The Transaction Cost Economics theory argues digitalisation reduces the costs associated with economic exchanges, such as gathering information, negotiating agreements, and monitoring performance. This improves market efficiency and facilitates better decision-making (Fern´andez-Portillo et al., 2020).

The digitalisation of informal sector enterprises foster innovation, reducing costs, and enabling more efficient production and distribution process, can improve firm's TFP (Biagi, 2013). Digital technology plays a crucial role in driving innovation and upgrading products and services within firms (Smith & Johnson, 2023). Its implementation extends beyond enhancing operational efficiency to fostering the evolution of business models and the continuous renewal of product offerings. By leveraging data-driven decision-making, firms can obtain precise insights into market demands, enabling them to develop targeted products and services, ultimately contributing to increased total factor productivity (Smith & Davis, 2022). Additionally, digital technology significantly enhances customer experience and facilitates market expansion by enabling firms to gain deeper insights into consumer preferences, implement personalized solutions, and improve overall customer satisfaction (Smith & Johnson, 2023). Internally, digital adoption optimizes resource allocation and production efficiency, while externally, it strengthens firms' ability to strategically position their supply-side operations and enhance both the quality and effectiveness of their offerings. However, the benefits of digital transformation do not materialize instantaneously. The process of digital adoption and integration is complex and long-term, and its impact on firm performance may not be immediately evident (Guo et al., 2023). However, Carr (2003) and Gordon (2000) suggest that productivity gain from being digitalised is short-lived.

2.3 Financial Inclusion and Digitalisation in Informal Sector Enterprises

Financial inclusion has emerged as a fundamental policy priority for governments worldwide, gaining significant attention among policymakers, academicians, and practitioners due to its crucial role in fostering economic development and reducing financial disparities. It primarily focuses on eliminating barriers that hinder individuals and businesses from accessing essential financial products and services, such as credit, investment opportunities, savings mechanisms, insurance, financial technology, and payment systems, thereby ensuring that all economic participants can engage in formal financial activities without restrictions (Abor et al., 2020). The overarching objective of financial inclusion is to enhance individuals' access to regulated financial services, particularly by promoting the adoption of formal bank accounts, which serve as a gateway to broader financial participation. This, in turn, plays a vital role in poverty alleviation and overall economic growth, as increased financial access empowers individuals and businesses to manage resources efficiently, invest in productive activities, and mitigate financial risks (Ozili, 2018). This highlights, the core aim of financial inclusion is to provide financial services and products at an affordable cost, particularly to marginalised and economically vulnerable populations who have historically been excluded from the formal financial sector.

In most developing countries, financial inclusion and access to finance have historically been low. However, the introduction of mobile money banking has gradually improved this situation, offering greater accessibility to financial services and enhancing economic opportunities. Informal sector enterprises in many developing countries face numerous economic challenges and inefficiencies. These enterprises often struggle with inadequate infrastructure, unreliable energy supply, and limited access to markets, making it difficult to sustain and expand their operations. Additionally, they encounter regulatory constraints such as complex tax requirements, restricted access to financial resources, and high transportation costs. The small market size and high information costs further add to their difficulties. Moreover, macroeconomic instability creates an unpredictable business environment, increasing their vulnerability and limiting their long-term growth prospects (Shekar et al., 2023; Sleuwaegen & Goedhuys, 2002).

The rapid advancement of digital technology has significantly influenced financial inclusion, particularly in the informal sector, by enhancing access to financial services and improving business operations. Digital financial services, such as mobile banking, digital payments, and fintech-driven credit mechanisms, have emerged as vital tools in bridging the financial gap for informal enterprises. Studies indicate that mobile money services have played a crucial role in increasing financial accessibility, particularly in developing economies, where traditional banking infrastructure is often inadequate (Demirgüç-Kunt et al., 2018). Digital payment systems, including mobile wallets and Unified Payments Interface (UPI), have enabled informal enterprises to conduct transactions more efficiently, reducing dependence on cash-based systems and enhancing business transparency.

Moreover, digital lending platforms have revolutionized credit access for informal sector enterprises by leveraging alternative credit scoring mechanisms, such as transaction history and behavioural data, to assess creditworthiness (Sanga & Aziakpono, 2023). These innovations have helped overcome traditional barriers to credit, such as lack of collateral and formal financial records, which have historically limited the financial inclusion of micro and small enterprises. In addition to credit and payments, digital platforms have facilitated access to savings and insurance products, further strengthening financial resilience among informal businesses (Ozili and Syed, 2024).

2.4 Informal sector, COVID-19 pandemic and Digitalisation

The COVID-19 outbreak, officially declared a pandemic by the World Health Organization on March 11, 2020, posed significant challenges to global health systems and had far-reaching consequences for labour markets worldwide. As countries grappled with the rapid spread of the virus, healthcare infrastructure faced unprecedented pressure, with hospitals and medical personnel struggling to manage rising infection rates. Simultaneously, the pandemic led to disruptions in economic activities, altering working conditions across various sectors. Lockdowns, social distancing measures, and travel restrictions forced businesses to adopt remote work models, while industries dependent on physical labour, such as manufacturing, retail, and hospitality, experienced severe setbacks. The crisis disproportionately affected informal and vulnerable workers, exacerbating existing inequalities in job security, wages, and access to financial support. The International Labour Organization (ILO) reported in 2020 that the COVID-19 pandemic placed over 25 million jobs at risk globally. In India, data from the Centre for Monitoring Indian Economy (CMIE) indicated that nearly 122 million individuals lost their jobs by April 2020. The hardest-hit groups were wage labourers from micro, small, and own-account enterprises, as well as casual workers and small traders within the informal economy. This economic downturn further deepened poverty in the informal sector, making it increasingly difficult for affected workers to meet their basic needs (Dutta and Kar, 2022).

The COVID-19 pandemic triggered an unprecedented global economic downturn, significantly impacting productivity, business operations, and the adoption of digital technologies. According to the Organisation for Economic Co-operation and Development (OECD, 2020), the crisis accelerated the digital transformation of both public and private sector activities across various countries. This shift was reflected in advancements such as improved broadband connectivity, the widespread adoption of online business models, the promotion of digital payment systems, and the development of digital skills. A substantial proportion of firms integrated new digital technologies during this period, with larger, more digitally advanced, and highly productive firms being more inclined to implement such innovations in 2020 and 2021. Furthermore, businesses that had already invested in complementary technologies before the pandemic were more likely to adopt digital solutions that gained prominence during the crisis, including digital commerce platforms, collaborative software, cloud computing, and data analytics (Calvino et al., 2024).

The COVID-19 pandemic has accelerated the adoption of digital tools among informal businesses, transforming various aspects of their operations, including logistics, accounting, payments, and marketing. A survey conducted by the UNDP Accelerator Lab highlights that in the Global South, 90 percent of micro and small enterprises utilize digital tools. Notably, female entrepreneurs demonstrate a higher level of digital engagement; however, they continue to face challenges in formalizing their businesses. The survey further indicates that the integration of digital technologies among informal enterprises in the Global South has led to improvements in efficiency and productivity. Despite these advancements, the benefits of digitalisation are not equally distributed. Entrepreneurs with limited digital skills, particularly informal sector, encounter significant obstacles in leveraging digital transformation to its full potential (Dutta et al., 2023)

Our study adds to the existing literature on digitalisation of informal sector by offering empirical evidence from India, specifically examining how digitalisation influences financial inclusion and firm performance among informal enterprises pre and post COVID-19 pandemic. Given the significant disruptions caused by the pandemic, the role of digital financial services became even more critical in sustaining business operations, enabling access to credit, and facilitating transactions for firms operating in the informal sector. By analysing this relationship, our research highlights the extent to which digitalisation has contributed to bridging financial gaps and enhancing business resilience in a challenging economic environment. Existing research has largely explored the relationship between digitalisation and financial inclusion across various country contexts. However, studies specifically examining this nexus within informal enterprises in India remain limited. A notable exception is the work of Dutta, Kar and Guha (2023), which investigates the link between digital technology adoption and firm performance in India's informal sector using data from the World Bank Enterprise Survey (WBES). While their study provides valuable insights, our research offers both methodological and data-related advantages. We utilize nationally representative large-scale survey data from the 2016 and 2023 rounds of the Survey of Unincorporated Non-Agricultural Enterprises, allowing for a more rigorous analysis of digitalisation trends over time. Additionally, our empirical framework employs the Difference-in-Differences (DID) approach, which strengthens the methodological rigor of our study by effectively addressing potential endogeneity concerns and capturing the causal impact of digitalisation on financial inclusion and firm performance in the informal sector in Indian context. The study also included a detailed disaggregated analysis based on activity type and enterprise classification, enhancing the robustness and depth of the research findings. By using these methodological and data-related strengths, our research contributes to a deeper understanding of how digitalisation influences financial inclusion among informal enterprises in India, particularly in the post-pandemic economic landscape.

3 Data, Variables and Method

This study draws upon pre covid data from the National Sample Survey Office (NSSO) survey on unincorporated non-agricultural enterprises (2015–16) and the most recent Annual Survey of Unincorporated Sector Enterprises (ASUSE), 2022–23 for Post covid. These surveys have covered a large number of unincorporated non-agricultural enterprises[2] comprising manufacturing, trade, and service enterprises (excluding construction) at the national and state levels. And it has information on the operational and economic characteristics of the enterprises. The operational characteristics of the enterprises mainly cover the ownership pattern, type of enterprises, nature of operation, status of registration, employment, etc. Whereas the economic characteristics consist of the operating expenses and receipts of an enterprise, the values of owned and hired fixed assets, payments to the workers, and the loan characteristics of the firms.

The 73rd round of the survey conducted in 2015-16 covered a total of 290,113 enterprises, with 143,179 located in rural areas and 146,934 in urban areas. In the more recent ASUSE 2022-23 survey round, the sample size was significantly expanded to 458,938 enterprises, comprising 258,296 in rural regions and 200,642 in urban areas. For this study, data from both survey rounds have been utilized to analyse the relationship between digitalisation, financial inclusion, and firm performance, with a specific emphasis on changes observed before and after the COVID-19 pandemic. By using these two survey datasets, this research aims to provide a nuanced understanding of how digital adoption has influenced financial inclusion and firm performance in the informal sector over time. The inclusion of both pre-pandemic and post-pandemic data allows for a more robust comparative analysis, making these survey sources highly relevant to the study's objectives.

For the firm performance indicators, we have measured total factor productivity at firm level (TFP) using a standard parametric Cobb-Douglas production function of the following form (Please refer Appendix Table A1 for the results):

$$\ln Q_{it} = \text{In } A_{it} + \alpha \text{In} K_{it} + \beta \text{In} L_{it} + \varepsilon_{it}$$

Where Q_{it} =log of output (Gross value added); A_{it}= Total Factor Productivity (TFP);

[2] *According to the definition by NSSO, unincorporated non-agricultural enterprises are those which are not registered under companies' act of 1956 and it excludes those enterprises which are registered under the factories act of 1948, Bidi and Cigar workers act of 1966 and the public enterprises and the cooperatives.*

K_{it} = log of capital stock (Gross fixed assets); L_{it}= log of labour force (number of workers); ε_{it}=Random error term

In addition, labour productivity as another proxy for firm performance is calculated as Gross value added (deflated values) of the firm divided by total number of the workers. The GVA values of both the years are subsequently adjusted for inflation using industry-specific value-added deflators for the base year 2011–2012. Each firm is first matched to its corresponding industry group, and the appropriate deflator is then applied. These deflators are sourced from the India KLEMS database (2024) and cover manufacturing, trade, and nine specific service sectors such as electricity; transport and storage; post and telecommunications; hotels and restaurants; financial and insurance services; business services; education; health, healthcare and social work; and other services.

In order to construct a Digitalisation Index, a summation method was employed using multiple binary indicators that capture various dimensions of digital adoption within enterprises. The index was generated by aggregating 20 digitalisation components, each representing a specific aspect of digital engagement, including Internet, web presence, intranet usage, online sales and purchases, internet access types (narrowband, fixed broadband, mobile broadband), networking infrastructure (LAN, extranet), email usage, telephonic internet, access to online information, interactions with government organizations, internet banking, online financial transactions, digital customer interactions, online service delivery, online recruitment, and online training. These components were summed and then normalised by dividing by the total number of indicators (20), ensuring that the Digitalisation Index ranged between 0 and 1.

To further categorise enterprises into high and low digitalisation groups, a binary classification was introduced. The mean value of the Digitalisation Index was computed, and enterprises with an index value above the mean were classified as highly digitalised (digitsum_index_dummy =1), while those at or below the mean were classified as low digitalized (digitsum_index_dummy = 0).

To measure financial inclusion among firms, a Summation Index of Financial Inclusion is developed using several key indicators of access to formal financial services. This index is constructed based on multiple dimensions of financial accessibility, represented by binary variables. These include access to credit from central and state-level term lending institutions, commercial banks, cooperative banks and societies, microfinance institutions, and other institutional agencies. Each of these variables is assigned a value of 1 if the firm has availed financial services from the respective source and 0 otherwise. Additionally, bank account ownership is also incorporated as a binary variable, where a value of 1 indicates that the firm holds a bank account, and 0 otherwise. The financial inclusion index is then created by summing these individual binary variables.

We have incorporated several control variables to account for key firm-level characteristics. Additionally, industry and state fixed effects were included in the model to control for unobserved heterogeneity across sectors and regions. A detailed description of these control variables is provided in Appendix Table A2.

3.1 Method

Digitalisation impact is considered as an exogenous treatment, given that the post-COVID-19 period forced informal sector firms to widely adopt digital technologies as a survival strategy rather than as a purely endogenous decision driven by firm-specific characteristics (Bhattacharjee et al., 2024; Shekar & Mansoor 2021). The COVID-19 pandemic disrupted traditional business operations, creating an urgent need for firms to integrate digital payment systems, online transactions, and remote working tools to maintain continuity (Shekar & Mansoor 2021). This widespread shift was primarily dictated by external constraints such as lockdown measures, supply chain disruptions, and changes in consumer behaviour rather than firms' pre-existing productivity or financial capacity. Additionally, government policies[3] and financial institutions actively promoted digital adoption through incentives and regulatory frameworks, further reinforcing the argument that post-COVID digitalisation was not entirely a choice but a necessary adjustment imposed by external shocks (Bhattacharjee et al., 2024; Shekar & Mansoor 2021). Given these circumstances, the variation in digital adoption across firms in the pre-COVID and post-COVID period can be reasonably treated as exogenous, as it primarily stems from pandemic-induced structural changes rather than firms' pre-determined characteristics or strategic decisions.

Thus, to estimate the impact of digitalisation on financial inclusion and productivity at firm level during pre and post covid, the Difference-in-Differences (DID) model is used. This

[3] During and post-COVID, the Indian government strengthened digitalization through initiatives like Direct Benefit Transfer (DBT), Unified Payments Interface (UPI) expansion, and Goods and Services Tax (GST) e-invoicing, making digital transactions essential. Schemes like PM SVANidhi for street vendors and Emergency Credit Line Guarantee Scheme (ECLGS) for MSMEs required digital compliance, while PM-WANI and Digital Banking Units (DBUs) enhanced financial inclusion. These policies ensured that digitalisation was not purely voluntary but a necessity driven by government regulations, financial incentives, and pandemic-induced constraints.

method is particularly suitable as it enables the decomposition of observed changes in firm performance following digitalisation into two key components: changes attributable to time-related trends and the direct impact of digital adoption. By distinguishing these effects, the DID model provides a robust framework for isolating the true influence of overtime effect of digitalisation on firm performance.

Given that the firms observed in the two survey rounds do not represent the same set of enterprises, identifying appropriate treatment and control groups presents a significant challenge. This hinders the direct application of the Difference-in-Differences (DID) approach for measuring the impact of digitalisation over time. To address this issue and ensure the suitability of the DID model, the study employs a methodological adjustment by converting the two independent cross-sectional datasets into a pseudo-panel framework, as proposed by Deaton (1985). This transformation is achieved through the use of the Propensity Score Matching (PSM) technique, which allows for the creation of comparable groups based on observable characteristics (Shekar, K.C. and Nataraj, M., 2023). By implementing this approach, the study ensures that the analysis accurately captures the effects of digitalisation on financial inclusion and firm performance while accounting for variations in firm characteristics across survey periods. Deaton (1985) demonstrated that independent cross-sectional surveys can be transformed into a synthetic or pseudo-panel by grouping observations with similar characteristics into cohorts[4]. In this study, we used two independent cross-sectional surveys where the firms included in each round are not identical, and the total number of firms differs between the survey periods. To construct a pseudo-panel and ensure comparability between the two datasets, we employ the PSM technique, which allows for the identification of cohorts with comparable characteristics across survey rounds.

In pseudo-panel analysis, cohorts represent average values for groups of homogeneous firms, making it a reasonable approximation of the population mean, albeit with some degree of measurement error. To mitigate this concern, cohorts were constructed by selecting firms with a similar likelihood of adopting digitalisation across the two survey periods. The PSM technique was implemented in three sequential steps to ensure robustness in the cohort formation process. In the initial step, the unit-level data from the NSS Unincorporated Enterprise Survey, 73rd Round (2016), was used as the baseline year, while the ASUSE 2023

[4] Deaton (1985) contends that employing pseudo-panel data does not inherently lead to less reliable results compared to traditional panel data, as the measurement errors associated with pseudo-panels are relatively limited.

dataset was considered for the follow-up year for the analysis. These two survey rounds represent the most recent available data and are separated by a seven-year interval. This time gap is deemed sufficient for capturing the long-term impact of digitalisation on firm performance.

In the second step, the treatment and control groups for the baseline year (2016) are identified. To ensure that any differences in firm performance between these groups can be attributed solely to the intervention i.e., digitalisation, it is essential to verify that their characteristics are comparable. Initially, firms are classified into treatment and control groups based on whether they have adopted digitalisation. Following this classification, the PSM technique, a quasi-experimental method proposed by Gertler et al. (2011), is applied to establish comparability between the two groups. Propensity scores are then estimated for both treatment and control groups using a logit model for the baseline year. This model calculates the probability of a firm engaging in digitalisation based on firm level characteristics.

Number of methods are available for estimating the conditional probability of receiving treatment using a vector of observed covariates. These methods include logistic regression, the probit model, and discriminant analysis. Out of which, logistic regression is the prevailing approach (Guo et al., 2020) which allows to calculate how similar the high digitalised and low digitalised firms are with respect to other covariates. The estimation procedure of logistic regression ensures that probabilities are bounded in between 0 and 1.

Therefore, we used logistic regression model for the estimation of the propensity score with dependent variable (*D*) as digitalisation which takes the value 1 (*D=1*) if the firm is highly digitalised and 0 (*D=0*) is low digitalised (Rosenbaum & Rubin, 1983). The specification of this model is presented in Equation (1).

$$P(X) = \Pr(D = 1 \mid X) \ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(1)}$$

Where *X* represent the vector of covariates, including enterprise type, gender and caste of the owner, rural and urban, subcontracting, accounts maintained, age of the firm, average of workers, capital values, state and industry controls. According to Resenbaum (2002) we can only use the covariates that are significantly different between two groups. By incorporating large set of interrelated and diverse covariates can mitigate the negative effects of excluding an unobserved covariate by including available variables that are associated with the unobserved factors (Stone & Tang, 2019).

Table 1 Logit Regression Results

Variables	2016		2023	
	Coeff	SE	Coeff	SE
Home Ent	-0.25	(0.187)	-0.13***	(0.025)
Female	0.09	(0.160)	-0.08**	(0.030)
Rural	-0.28**	(0.115)	-0.13***	(0.018)
SC/ST	-0.35	(0.248)	-0.26***	(0.032)
OBC	-0.10	(0.126)	-0.26***	(0.020)
OAEs	0.11	(0.608)	-0.58***	(0.023)
Subcontract	0.30	(0.315)	0.23***	(0.076)
Acc.maintained	0.49***	(0.175)	0.96***	(0.028)
Age of firm	-1.40	(1.016)	-0.90***	(0.087)
Avg. workers	91.61***	(19.570)	110.07***	(9.000)
Capital value	31.12	(31.079)	262.07***	(55.420)
State dummy	Yes		Yes	
Industry dummy	Yes		Yes	
Constant	-1.29**	(0.529)	-1.69***	(0.085)
Observations	35,210		58,721	
Pseudo R2	0.143		0.235	
Wald Ï‡2	302.8		17005	
Log Likelihood	-1292		-42240	

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

In pre COVID period i.e., 2016, the logit regression results indicate that home-based enterprises had a negative but statistically insignificant association with high digitalisation (-0.25), implying that operating from home did not significantly influence digital adoption at that time. Female-owned enterprises showed a small positive coefficient (0.09), but this was not statistically significant, indicating that gender did not play a major role in digital adoption. Rural firms, however, faced a significant disadvantage in adopting digitalisation (-0.28, $p < 0.05$), suggesting that urban enterprises were more likely to be digitalized. Caste disparities were evident, with SC/ST firms showing a negative but insignificant coefficient (-0.35), while OBC-owned firms also exhibited a small negative but insignificant coefficient (-0.10), suggesting that caste was not a strong determinant of digitalisation in 2016. Own-account enterprises (OAEs) displayed no significant relationship with digitalisation (0.11), and firms engaged in subcontracting showed a positive but statistically insignificant coefficient (0.30). The results indicate that maintaining financial accounts had a significant positive impact on digital adoption, as firms that kept proper accounts were more likely to be digitalized (0.49, $p < 0.01$). Older firms were negatively associated with digitalisation, but the coefficient (-1.40) was not statistically significant, implying that firm age did not strongly influence digital adoption. Larger firms, as measured by the number of workers, were significantly more likely to be digitalized (91.61, $p < 0.01$), indicating that firm size played a crucial role in digital adoption. Capital investment did not show a significant impact on digitalisation in 2016 (31.12).

In post COVID period i.e., 2023, the logit regression results show a stronger and more structured pattern of digital adoption. Home-based enterprises continued to face a significant negative association with digitalisation (-0.13, $p < 0.01$), suggesting that operating from home increasingly limited digital adoption. Female entrepreneurs, who showed no significant disadvantage in 2016, now had a significantly negative coefficient (-0.08, $p < 0.05$), indicating that gender barriers to digitalisation had intensified. Rural firms continued to lag in digital adoption (-0.13, $p < 0.01$), reinforcing the urban-rural divide in access to digital technology. Caste disparities became more pronounced, with SC/ST firms showing a significant negative coefficient (-0.26, $p < 0.01$), suggesting that marginalised communities faced greater barriers to digital adoption in 2023. Similarly, OBC-owned firms, which were not significantly disadvantaged in 2016, now exhibited a strong negative association with digitalisation (-0.26, $p < 0.01$). Own-account enterprises (OAEs) also faced significant challenges in adopting digitalisation, with a strong negative coefficient (-0.58, $p < 0.01$), implying that smaller businesses struggled more with digital adoption. In contrast, firms engaged in subcontracting saw a significant positive association with digitalisation (0.23, $p < 0.01$), suggesting that subcontracted firms were more likely to adopt digital technologies in 2023. The impact of financial discipline remained strong, with firms maintaining proper accounts being significantly more likely to be digitalized (0.96, $p < 0.01$). Older firms showed a strong negative association with digitalisation (-0.90, $p < 0.01$), implying that newer firms were more inclined towards digital adoption. Larger firms continued to have a strong positive impact on digital adoption (110.07, $p < 0.01$), further reinforcing the importance of firm size in digitalisation. Unlike in 2016, capital investment emerged as a crucial determinant of digital adoption in 2023, with a highly significant positive coefficient (262.07, $p < 0.01$), indicating that firms with greater capital investment were more likely to adopt digitalisation. The overall model fit improved significantly in 2023, with Pseudo R^2 increasing to 0.235, a dramatic rise in the Wald χ^2 statistic to 17,005, and a lower Log Likelihood of -42,240, demonstrating a stronger explanatory power of the model in capturing the determinants of digital adoption. These results suggest that digitalisation in 2023 was increasingly shaped by firm characteristics, financial discipline, and structural disparities, with larger and more capitalized firms benefiting the most from digital adoption.

The predicted value of the logit model provides the propensity score of individual firms to engage in digitalisation. To ensure that the control and the treated groups are similar in their characteristics, the propensity scores are matched between the two groups using the single nearest neighbourhood, with replacement, matching technique (Abadie and Imbens, 2006; (Shekar, K.C. and Nataraj, M., 2023). Further, only those firms which are falling in the common support region are considered for matching. The common support region is the region where there is an overlap in the propensity score between the treatment and the control group. In other words, it is the region within the maximin and the minimax of the propensity scores between the digitalised and the non-non-digitalised firms.

The maximum and minimum values of propensity scores are -3.49 and 16.40 for high digitalised firms and for low digitalised firms are -5.80 and 8.24 respectively. The common support range is represented as:

$$[common_{min}, common_{max}] \\ = [\max(min_{high\ digitalised}, min_{low\ digitalised}), \min(max_{high\ digitalised}, max_{low\ digitalised})]$$

Firms with PS scores outside this range are excluded from the matching. The common support ranges from -3.49 to 8.24.

$$Within\ common\ support = \begin{cases} 1, if\ common_{min} \leq\ PScore_i \leq common_{max} \\ 0, otherwise \end{cases}$$

We used the nearest-neighbour matching (Heckman et al., 1997) with a caliper of 0.05 and with replacement to pair the high digitalised firms and low digitalised firms based on the propensity scores. This method aims to match the high digitalised firms to low digitalised firms.

Additionally, the mean difference in the characteristics of the two groups are analysed by the balancing t-test. Table shows the results of the t-test between the two groups before and after the matching. The null being that there is no difference in mean between the treated and the control groups.

Table 2 Balancing t test in difference of covariate means at base year 2016

Variable	Pre-Match	In-Match	Percent reduction in bias (%)
Home Ent.	-3.08***	0.10	96.1
Female	-0.51	-0.17	57.1
Rural	-6.14***	1.69*	66.0
SC/ST	-2.00**	-0.41	74.8
OBC	-1.76*	0.99	29.6
OAEs	-0.74	-0.54	18.9
Subcontract	1.99**	-0.68	57.2
Acc.maintained	5.30***	0.54	88.2
Age of firm	-0.23	-0.15	14.7
Avg. workers	2.84***	1.07	89.9
Capital value	4.03***	-0.17	97.4

Source: Same as in Figure 1

The balancing t-test assesses whether the differences in characteristics between the treatment and control groups have been minimized after propensity score matching. The pre-match results indicate significant differences in several characteristics, such as home enterprise status, rural location, SC/ST affiliation, subcontracting, accounting maintenance, average number of workers, and capital value, suggesting an initial imbalance between digitalized and non-digitalized firms. However, after matching, most of these differences become statistically insignificant, demonstrating that the matching process successfully balanced the two groups. The percent reduction in bias further highlights the effectiveness of this approach, with substantial reductions observed in capital value (97.4 percent), home enterprise status (96.1 percent), and accounting maintenance (88.2 percent). This suggests that the matching procedure effectively minimizes systematic differences between the groups, ensuring that the observed variations in firm performance post-digitalisation are primarily attributable to digitalisation itself rather than pre-existing disparities. While certain variables, such as OAEs and age of the firm, exhibit relatively lower reductions in bias, the overall results confirm that the matching process has enhanced comparability between the treatment and control groups in pre COVID baseline year (2016).

The third step is to identify the treatment and the control group from the post COVID follow-up year (2023). Here the issue is twofold. The first requirement is to ensure that the characteristics of the high digitalised firms and the low digitalised firms in 2023 matches with their corresponding counterparts in pre COVID baseline year (2016). By matching the set of control and treatment groups between the two time periods, one can reflect on the over-time effect of digitalisation on the financial inclusion and firm performance. Second requirement is to match the firm characteristics of the control and the treatment group within 2023[5]. The propensity scores of the firms in the follow up year are retrieved from the logit model with exact specifications as that of equation 1 (See Table 1). Then those firms are considered from the follow up year whose propensity scores are within the common support region of the pre COVID baseline year (2016). This ensures that the control and the treated group of the follow up year matches with their counterparts in the base year (Shekar, K.C. and Nataraj, M., 2023).

The matching of the control and the treatment group within 2023 is performed in a similar way as that of 2016 using the same PSM technique, but for the observations matched with their counterparts in the base line year (See Table 3). It should be noted that the mean propensity score of the matched firms in the pre COVID baseline period (2016) is very close to that for finally selected target firms in post COVID followup year (2023).

Table 3 Balancing t test in difference of covariate means at base year 2023

Variable	Pre-Match	In-Match	Percent reduction in bias (%)
Home Ent.	-18.39***	-0.20	98.5
Female	-22.61***	0.49	97.2
Rural	-4.92***	-0.64	81.8
SC/ST	-12.45***	0.12	98.7
OBC	-15.41***	0.34	96.9
OAEs	-54.64***	-0.08	99.8
Subcontract	4.39***	0.04	98.6
Acc.maintained	68.15***	-0.36	99.1
Age of firm	-4.74***	0.27	91.9
Avg. workers	53.88***	2.89***	92.5
Capital value	38.59***	2.82***	90.6

[5] In order to achieve this over time matching of the propensity scores, it is necessary to ensure that the propensity scores are comparable between the two time periods. This is taken care of by normalising the variables-capital value, average number of workers and the age of the firm before being used in the logit regression for both the time periods.

Source: Same as in Figure 1

The balancing t-test results indicate that, before matching, there were significant differences between the treatment and control groups across multiple variables, suggesting an initial imbalance. However, after matching, the differences in most variables become statistically insignificant, demonstrating that the propensity score matching process effectively improved comparability between digitalized and non-digitalized firms. The percent reduction in bias is substantial for key variables such as OAEs (99.8 percent), accounting maintenance (99.1 percent), and SC/ST status (98.7 percent), confirming that the matching procedure successfully minimized systematic differences. While some variables, like average workers and capital value, still show slight post-match differences, the overall reduction in bias ensures that any observed effects on firm performance can be more confidently attributed to digitalisation rather than pre-existing disparities.

A total of 89976 firms with 32253 firms in 2016 and 57753 firms in 2023 met both the matching selection criteria. After finalising the control and the treatment group for both the years, we performed the Card and Kruger’s (2000) difference in difference (DID) model. This exercise is executed for manufacturing, Trade and Services and also for Own Account Enterprises (OAE) and Establishment (EST). The firm performance is captured by labour productivity and Total Factor Productivity (TFP).

The model specification of the DID model is the following.

$$Y_i = \alpha + \beta T_i + \gamma t_i + \delta(T_i \times t_i) + \epsilon_i \text{ …..(2)}$$

Here Y_i is the outcome variable which is *Financial inclusion index, Labour productivity and Total Factor Productivity (TFP).* T_i is the intervention dummy, which takes the value of 1 when the firm has engaged in high digitalisation and 0, otherwise. t_i is the time dummy, which takes the value 1 when the year is the post COVID follow-up year (2023) and 0 when the year is pre COVID baseline year (2016). β account for the average differences in the outcome variable between the high digitalised and the low digitalised firms. γ captures the permanent mean difference in the outcome variable between 2016 and 2023, depicting the trend of the outcome variable over the two time periods. δ depicts the difference in the over-time change of the outcome variable between the high digitalised and the low digitalised firms. In other words, δ is the DID indicator which represents how the digitalised firms have performed from 2016 to 2023 in comparison to that of the low digitalised firms. ϵ_i is the error term.

The mean value of the outcome variables for the four groups of firms are stated in equation 3 to 6.

Group 1: Mean of outcome variables for the digitalised firms in the pre COVID baseline year (2016);

$$E(Y_i|T_i = 1 \; and \; t_i = 0) = \alpha + \beta \quad ……(3)$$

Group 2: Mean of outcome variables for the high digitalised firms in the post COVID follow-up year (2023);

$$E(Y_i|T_i = 1 \; and \; t_i = 1) = \alpha + \beta + \gamma + \delta \qquad ……(4)$$

Group 3: Mean of outcome variables for the less digitalised firms in the pre COVID baseline year (2016).;

$$E(Y_i|T_i = 0 \; and \; t_i = 0) = \alpha \quad …………..(5)$$

Group 4: Mean of outcome variables for the less digitalised firms in the post COVID follow-up year (2023);

$$E(Y_i|T_i = 0 \; and \; t_i = 1) = \alpha + \gamma \quad ……(6)$$

Equation (6) minus Equation (5) estimate the over-time change in the mean value of the outcome variable for the less digitalised firms. It takes the value, γ . Similarly, equation (4) minus equation (3) estimates the over-time change in the mean value of the outcome variable for the high digitalised firms. It takes the value $\gamma + \delta$. Now, the difference in the over-time changes of the mean value of the outcome variable between the high digitalised and the low digitalised firm is $(\gamma + \delta - \gamma) = \delta$. Hence δ is the DID indicator or the 'double difference' indicator.

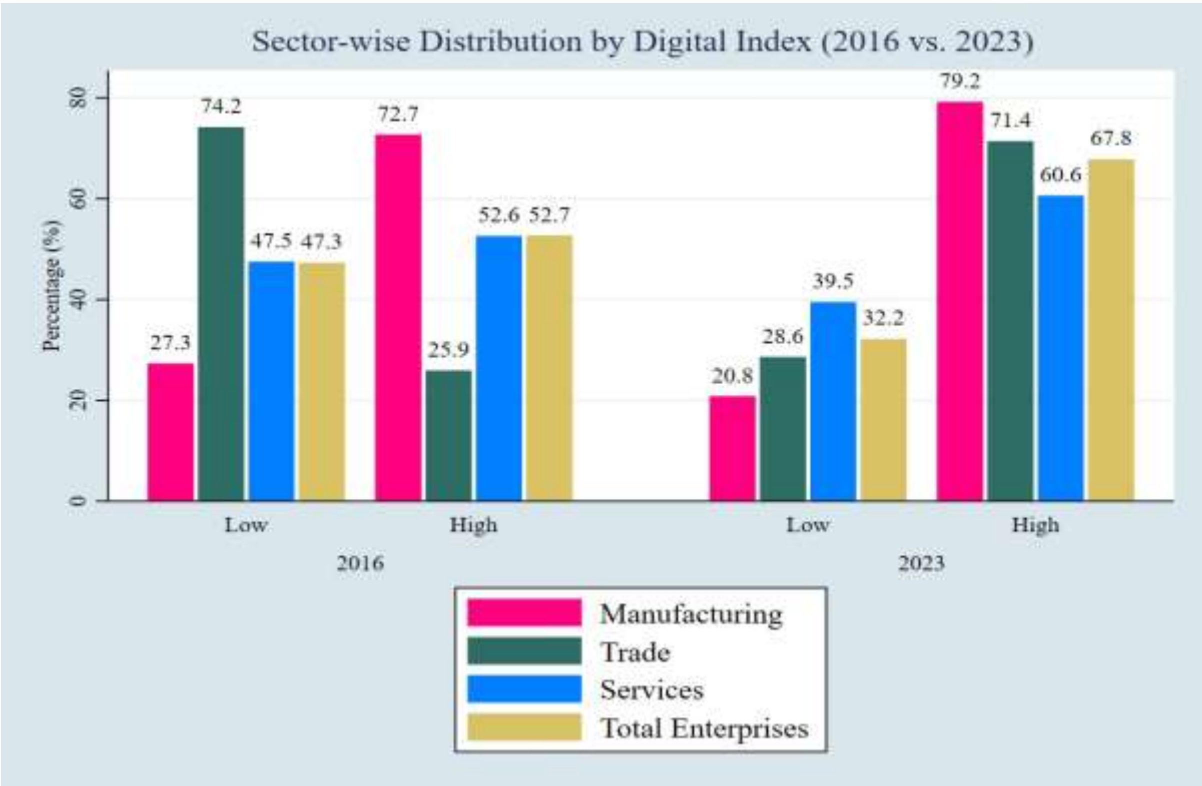
4. Descriptive analysis

Figure 1: Distribution of Digital indicators among informal enterprises in India

Source: Same as in figure 1

In figure 1, between 2016 and 2023, the digital engagement of informal enterprises in India underwent considerable changes. A notable increase was observed in the use of mobile broadband, which rose from 22.6 percent to 86.8 percent, indicating a substantial shift towards mobile-based internet connectivity. General internet usage expanded as well, growing from 4.0 percent to 21.1 percent, reflecting enhanced access to digital platforms. The use of internet banking also experienced a moderate rise, increasing from 56.3 percent to 61.2 percent, suggesting a gradual integration of digital financial services within informal business operations. In contrast, several other digital indicators recorded a decline. The use of fixed broadband connections decreased significantly from 62.2 percent to 12.7 percent, while reliance on email dropped from 79.5 percent to 25 percent, potentially due to the increasing adoption of mobile-based communication alternatives. Similarly, the proportion of enterprises maintaining a web presence declined from 46.6 percent to 29.2 percent, and intranet usage reduced sharply from 42.2 percent to 4.7 percent, indicating a move away from traditional internal networks. Interaction with government digital platforms also weakened; the use of online government services fell from 36.6 percent to 10.6 percent, and engagement with government portals declined from 24.6 percent to 6.5 percent. Furthermore, participation in online training activities dropped from 21.9 percent to 2.8 percent, while the use of online delivery services marginally decreased from 5.2 percent to 2.7 percent.

Figure 2: Percentage of low digitalised and high digitalised firms across the sectors

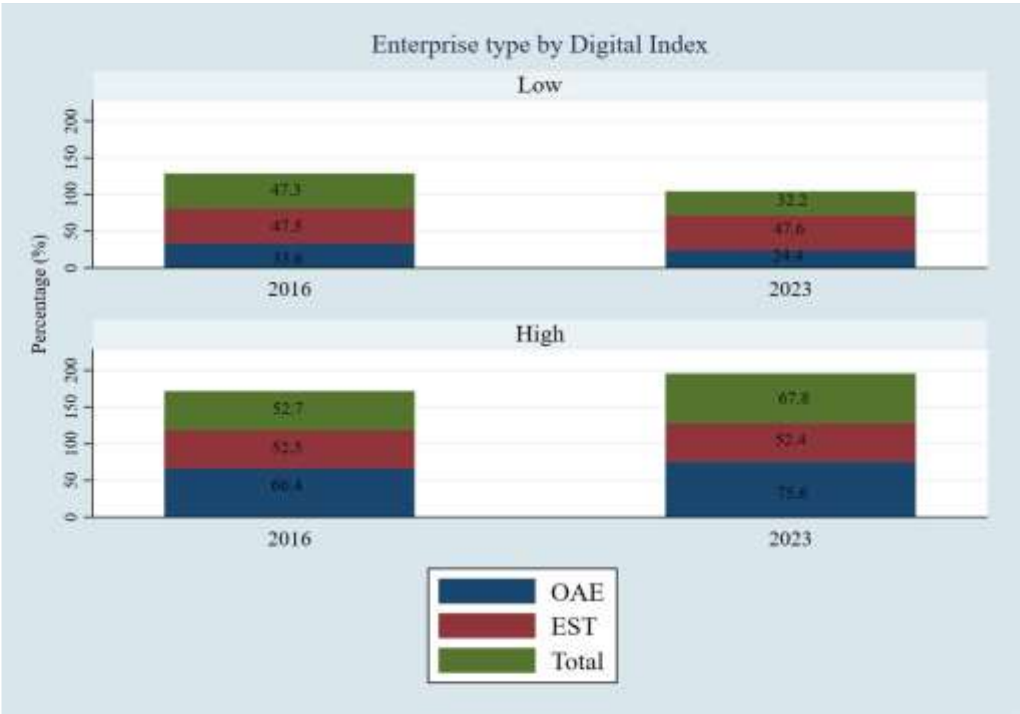


Source: Same as in figure 1

Figure 2 illustrates the sector-wise distribution of enterprises based on their level of digitalisation (low and high) for the years 2016 and 2023. The sectors considered include Manufacturing, Trade, Services, and Total Enterprises, categorized into two groups: Low Digitalisation and High Digitalisation. In 2016, a significant proportion of enterprises in the Trade sector (74.2%) fell into the low digitalisation category, whereas only 27.3% of Manufacturing enterprises were in this category. Conversely, enterprises in the Manufacturing sector were more likely to exhibit high digitalisation, with 72.7% classified under this group, compared to only 25.9% in Trade. Similarly, enterprises in the Services sector and the overall Total Enterprises category had a nearly equal distribution between low and high digitalisation, with approximately 47–52% in each category.

By 2023, a notable shift in digital adoption across sectors is observed. The proportion of low-digital enterprises declined across all sectors, particularly in Trade, where the percentage decreased from 74.2% in 2016 to 28.6% in 2023. At the same time, the share of high-digital enterprises increased substantially, with the Manufacturing sector experiencing the highest growth, reaching 79.2% in 2023. The Trade and Services sectors also witnessed a significant rise in the share of enterprises with high digitalisation, with 71.4% of Trade enterprises and 60.6% of Services enterprises classified as highly digitalized. The overall trend suggests a widespread transition towards higher digital adoption across sectors, with enterprises increasingly shifting from low to high digitalisation between 2016 and 2023. This transformation highlights the growing importance of digital technologies in business operations and the overall modernization of industries.

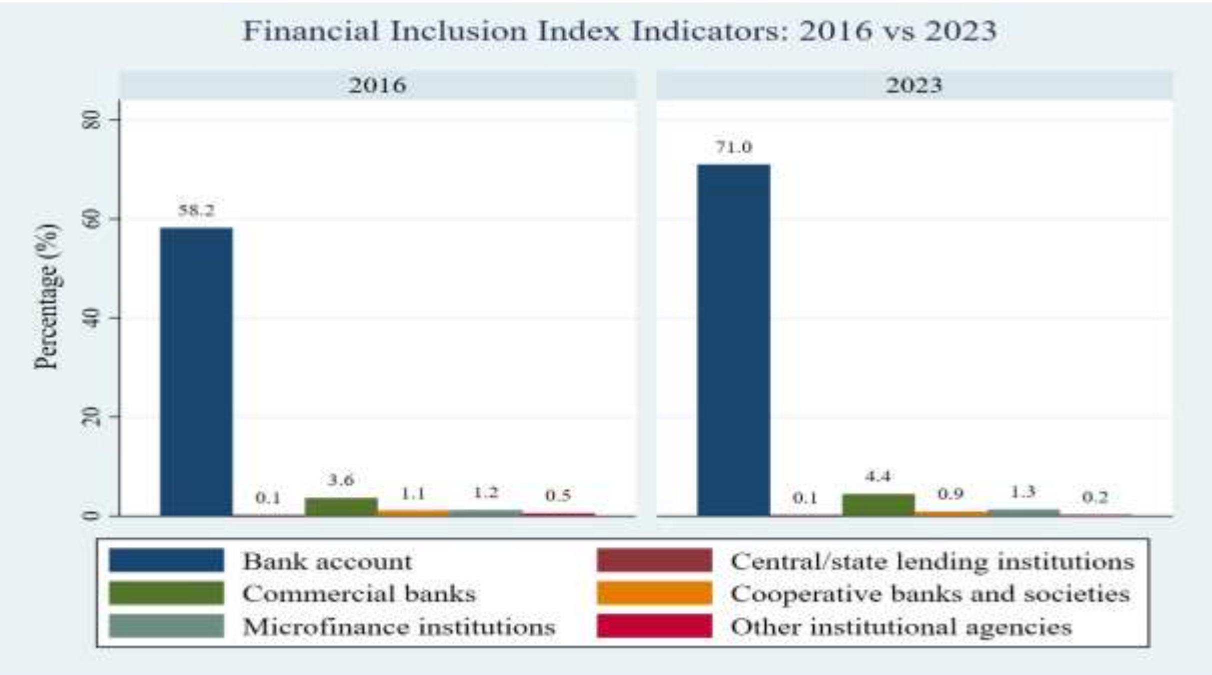
Figure 3: Distribution of enterprise by digitalisation index



Source: Same as in figure 1

Figure 3 presents the distribution of enterprise types by digitalisation index for the years 2016 and 2023, categorized into low digitalisation and high digitalisation groups. The enterprise types include OAE (Own-Account Enterprises), EST (Establishments), and the Total Enterprises. In 2016, within the low digitalisation category, OAE enterprises accounted for 33.6%, while EST enterprises comprised 47.5%, and the total percentage was 47.3%. By 2023, the proportion of low-digital enterprises had declined, particularly among OAE enterprises, which decreased to 24.4%. However, the EST category remained relatively stable at 47.6%, while the total share of low-digital enterprises reduced to 32.2%, indicating an overall shift towards higher digital adoption. For enterprises in the high digitalisation category, there was a clear upward trend in all enterprise types from 2016 to 2023. In 2016, 66.4% of OAE enterprises and 52.5% of EST enterprises fell under the high digitalisation category, contributing to a total of 52.7%. By 2023, this trend became more pronounced, with OAE enterprises increasing to 75.6%, EST enterprises remaining stable at 52.4%, and the overall share of highly digitalized enterprises rising to 67.8%. This shift suggests that enterprises, particularly OAE, have increasingly adopted digital technologies over time, contributing to a broader trend of digital transformation within the business landscape. Overall, the figure highlights a significant reduction in the share of enterprises with low digitalisation, accompanied by a substantial increase in the proportion of high-digital enterprises, particularly among OAE enterprises. This trend underscores the growing role of digital adoption in business operations, potentially improving efficiency, competitiveness, and overall enterprise performance.

Figure 4: Distribution of Financial inclusion indicators among informal enterprises in India



Source: Same as in figure 1

The below given figure 4 presents the distribution of various financial inclusion indicators across two time periods: 2016 and 2023. It highlights changes in the share of informal enterprises accessing financial services through different institutional sources. The indicators include access to bank accounts, credit from commercial banks, lending by central and state institutions, microfinance institutions, and other formal financial agencies.

It is evident from the figure that the share of informal sector enterprises having bank accounts increased largely between 2016 and 2023, reflecting broader penetration of basic financial services. Similarly, credit accessed from commercial banks and microfinance institutions shows a visible rise, indicating enhanced availability and use of credit from formal institutions. On the other hand, the contribution of central and state lending institutions and other institutional sources either remained stable or witnessed relatively smaller changes.

Table 4 Descriptive statistics by different firm characteristics

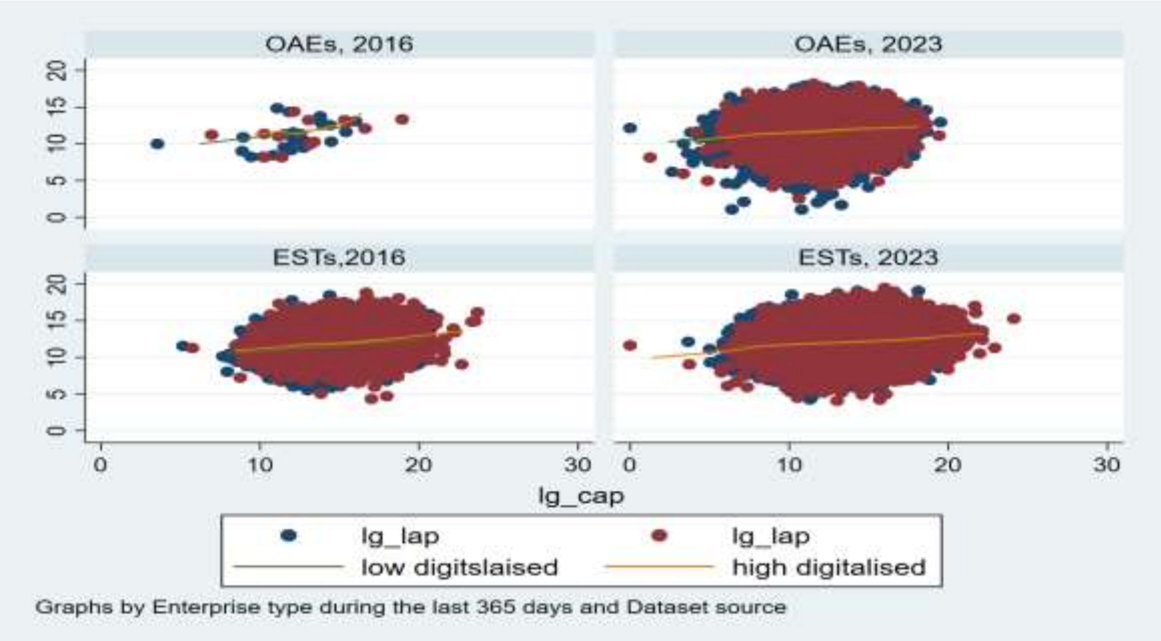
Firm characteristics	2016		2023	
	High digital	Low digital	High digital	Low digital
Home Ent.	70.3	29.7	76.6	23.4
Outside Ent.	57.4	42.6	67.9	32.1
Male	58.3	41.7	68.4	31.6
Female	63.5	36.5	79.5	20.5
OAEs	64.3	35.7	76.1	23.9
ESTs	58.5	41.5	56.3	43.7
Rural	73.3	26.7	75.1	24.9
Urban	55.2	44.8	67.3	32.7
SC/ST	64.3	35.7	77.3	22.7
OBC	63.7	36.3	72.4	27.6
Others	56.2	43.8	65.1	34.9
subcontract: Yes	74.6	25.4	64.7	35.3
subcontract: No	57.6	42.4	70	30
Acc. Maintain: Yes	55.3	44.7	41.1	59
Acc. Maintain: No	77.1	22.9	73.8	26.2
Total	58.8	41.3	70	30

Source: Same as in figure 1

The Table 4 provides a comparative analysis of firm characteristics by digitalisation level in 2016 and 2023, distinguishing between high digital and low digital firms. The data reveals a general increase in digital adoption across most categories over time. Home-based enterprises consistently exhibited higher digital adoption than outside enterprises, with the proportion of high-digital home enterprises rising from 70.3% in 2016 to 76.6% in 2023. Similarly, outside enterprises also experienced an increase in digitalisation, though to a lesser extent. Gender disparities in digital adoption are evident, with female-led enterprises showing a significant increase in high digitalisation from 63.5% in 2016 to 79.5% in 2023, whereas male-led enterprises also saw an improvement from 58.3% to 68.4%. In terms of enterprise structure, Own-Account Enterprises (OAEs) had a higher share of digital adoption compared to Establishments (ESTs), with OAEs increasing from 64.3% in 2016 to 76.1% in 2023, whereas ESTs experienced a slight decline in digitalisation over the same period. Rural and urban differences also persisted, with rural firms initially having higher digitalisation levels in 2016 (73.3%), but urban firms showing a more significant increase over time, reaching 67.3% in 2023. Social category-wise, Scheduled Castes/Scheduled Tribes (SC/ST) and Other Backward Classes (OBCs) demonstrated notable growth in digitalisation, with SC/ST enterprises increasing to 77.3% and OBC enterprises reaching 72.4% by 2023. Additionally, subcontracting firms saw a decline in high digitalisation, whereas non-subcontracting firms exhibited an increase. A striking trend is observed in account maintenance practices, where firms maintaining accounts had a lower digitalisation rate in 2023 (41.1%) compared to 2016 (55.3%), suggesting a potential shift in accounting and digitalisation practices. Overall, the data underscores a broad trend of increased digital adoption across most firm characteristics, with particularly notable improvements among female-led businesses, OAEs, and enterprises in socially disadvantaged groups.

In Figure 5 the effect of digitalisation is further analysed by comparing across the different types of enterprises at varying levels of capital endowments in the informal sector. It depicts that in general, high digitalised firms have comparatively high labour productivity than low digitalised firms. As the capital base increases (X axis), the gap between labour productivity of high digitalised and low digitalised firms has increased in both OAMEs and Establishments (Est) in pre covid period. However, the overtime effect (between pre and post COVID period) the gap between high digitalised and low digitalised has fade away for OAMEs and Establishments. This implies that the productivity gains among high digitalised and low digitalised firms have declined over time.

Figure 5: Changes in Labour productivity of high digitalised and low digitalised firms



Source: Same as in figure 1

5. Estimation results

5.1. *Impact of digitalisation on financial inclusion*

Tables 5, 6,7,8,9 and 10 shows the results of DID estimations for the impact of digitalisation on financial inclusion and firm performance. In these results, the first single-difference estimate reflects the gap between high and low digitalized firms in 2016 (pre COVID) and second single difference estimate indicate gap between high and low digitalized firms in 2023 (post COVID). The double-difference estimate (DID coefficient) estimate the net impact of digitalisation by comparing changes over time between high and low digitalised firms.

Table 5 presents the results of a Difference-in-Differences (DID) estimation, evaluating the impact of digitalisation on financial inclusion across different types of enterprises: All Enterprises, Establishments (EST), and Own-Account Enterprises (OAE). The first set of results corresponds to 2016, where low-digitalized enterprises exhibited estimated financial inclusion values of 1.048 for all enterprises, 1.015 for ESTs, and 0.855 for OAEs. Similarly, highly digitalised enterprises had estimated values of 1.049, 1.026, and 0.983, respectively. The single-difference estimate is found to be statistically insignificant across all categories, indicating that digitalisation had no significant influence on financial inclusion at this early stage. However, the results for 2023 reveal significant differences. The financial inclusion index for low-digitalised firms remained relatively stable, with values of 1.000 (All

Enterprises), 0.995 (ESTs), and 1.057 (OAEs), while the corresponding values for highly digitalised enterprises increased to 1.035, 1.013, and 1.103, respectively. The single-difference estimates in 2023 indicate a statistically significant positive impact of digitalisation, with coefficients of 0.035, 0.018, and 0.046, respectively, all significant at the 1% level. These findings suggest that enterprises with a higher degree of digitalisation experienced greater improvements in financial inclusion over time. The DID coefficient is 0.035 for all enterprises and is statistically significant at the 1% level. However, for ESTs, the coefficient is positive but not statistically significant, indicating a weaker effect of digitalisation in this category. In contrast, for OAEs, the DID coefficient is negative (-0.082) but statistically insignificant, suggesting that the financial inclusion benefits of digitalisation may have been less pronounced or unevenly distributed among smaller enterprises. These findings suggest that digitalisation has played a significant role in enhancing financial inclusion. However, the positive effects of high digitalisation on financial inclusion index tend to fade over time at disaggregate level in establishments and OAEs. This suggests that while digitalisation significantly positively associated with financial inclusion especially post COVID period, the overtime effect may diminish.

Table 5 Impact of digitalisation on financial inclusion by Enterprise type

Estimated impact	Estimated Values (Average of Logs)		
	All Enterprises	EST	OAE
Before			
Low digitalised in 2016	1.048	1.015	0.855
High digitalised in 2016	1.049	1.026	0.983
Single difference in 2016	0.001 (0.008)	0.011 (0.007)	0.128 (0.154)
After			
Low digitalised in 2023	1.000	0.995	1.057
High digitalised in 2023	1.035	1.013	1.103
Single difference in 2023	0.035***(0.002)	0.018*** (0.003)	0.046***(0.003)
Double difference	0.035***(0.008)	0.007 (0.008)	-0.082 (0.154)
Total observations	89976	35451	54525
R-square	0.07	0.05	0.09

*Source: Same as in Figure 1; Note: Robust Standard Error in Parenthesis; *P<0.1 **P<0.05 ***P<0.001*

Table 6 assesses the impact of digitalisation on financial inclusion across different major economic activities: Manufacturing, Trading, and Services. In 2016, the financial inclusion index for low digitalized enterprises stood at 0.179 for manufacturing, 0.164 for trading, and

0.162 for services, while the corresponding values for high digitalised enterprises were 0.178, 0.166, and 0.163, respectively. The single-difference estimates in 2016 were statistically insignificant. However, in 2023, the financial inclusion index for low digitalised enterprises either remained stable or slightly declined, with values of 0.173 (manufacturing), 0.164 (trading), and 0.153 (services). In contrast, the financial inclusion index for highly digitalised enterprises improved to 0.180, 0.166, and 0.161, respectively. The single-difference estimates in 2023 reveal a statistically significant positive effect of digitalisation, with coefficients of 0.007 (manufacturing), 0.002 (trading), and 0.008 (services), all significant at the 1% level. The results suggest that high digitalised enterprises experienced increase in financial inclusion compared to their low digitalised counterparts. The DID estimate shows a statistically significant positive effect for manufacturing (0.008) and services (0.007), both at the 1% level, indicating that digitalisation played a crucial role in enhancing financial inclusion in these sectors. However, the DID coefficient for trading (0.001) is statistically insignificant, implying that digitalisation did not have a substantial effect on financial inclusion within this sector. This highlights that digitalisation has had a significant and positive impact on financial inclusion, particularly in the manufacturing and services sectors, whereas its effect in trading remains weak.

Table 6 Impact of digitalisation on financial inclusion by Major activity

Estimated impact (coefficients)	Estimated Values (Average of Logs)		
	Manufacturing	Trading	Services
Before			
Low digitalised in 2016	0.179	0.164	0.162
High digitalised in 2016	0.178	0.166	0.163
Single difference in 2016	-0.001 (0.002)	0.001 (0.003)	0.001 (0.002)
After			
Low digitalised in 2023	0.173	0.164	0.153
High digitalised in 2023	0.180	0.166	0.161
Single difference in 2023	0.007*** (0.001)	0.002*** (0.001)	0.008*** (0.001)
Double difference	0.008*** (0.003)	0.001 (0.004)	0.007*** (0.002)
Total observations	15262	24374	50340
R-square	0.1	0.05	0.08

*Source: Same as in Figure 1; Note: Robust Standard Error in Parenthesis; *P<0.1 **P<0.05 ***P<0.001*

5.2 Impact of digitalisation on firm performance

Table 7 evaluates the impact of digitalisation on Total Factor Productivity (TFP) across different enterprise types: all enterprises, Establishments (ESTs), and Own-Account Enterprises (OAEs).

Table 7 Impact of digitalisation on Total Factor productivity by Enterprise type

Estimated impact (coefficients)	Estimated Values (Average of Logs)		
	All enterprises	EST	OAE
Before			
Low digitalised in 2016	0.13	0.586	1.431
High digitalised in 2016	0.454	0.843	1.292
Single difference in 2016	0.324*** (0.111)	0.257** (0.105)	-0.139 (0.49)
After			
Low digitalised in 2023	0.842	1.085	2.289
High digitalised in 2023	0.932	1.219	2.399
Single difference in 2023	0.09 (0.072)	0.133*** (0.021)	0.11 (1.06)
Double difference	-0.234 (0.148)	-0.123 (0.106)	0.249 (0.44)
Total observations	89869	35386	54483
R-square	0.01	0.08	0.01

*Source: Same as in Figure 1; Note: Robust Standard Error in Parenthesis; *P<0.1 **P<0.05 ***P<0.001*

In 2016, the estimated TFP values for low digitalised enterprises were 0.13 for all enterprises, 0.586 for ESTs, and 1.431 for OAEs, while for high digitalised enterprises, the values stood at 0.454, 0.843, and 1.292, respectively. The single difference in 2016 is statistically significant for all enterprises (0.324) and for ESTs (0.257), indicating that highly digitalised firms had a higher TFP than their low digitalised counterparts even before the digital transformation. However, the estimate for OAEs was negative (-0.139) and statistically insignificant, suggesting that digitalisation was not a key determinant of productivity for OAEs in pre COVID period.

However, in the post COVID year 2023, both low and high digitalised enterprises experienced a significant increase in TFP, with low digitalised enterprises reaching 0.842 (all enterprises), 1.085 (ESTs), and 2.289 (OAEs), while high digitalised enterprises achieved 0.932, 1.219, and 2.399, respectively. The single difference remained positive and statistically significant only for ESTs (0.133), implying that establishments benefited significantly from digitalisation in terms of productivity. For all enterprises (0.09) and OAEs (0.11), the estimates were not statistically insignificant, indicating that digitalisation did not lead to a substantial productivity gap in these groups during post COVID period.

The DID estimate is negative and statistically insignificant effect for all enterprises (-0.234) and ESTs (-0.123), suggesting that while digitalisation contributed to productivity gains in both groups, the relative advantage of high digitalised firms did not significantly increase over time. Interestingly, for OAEs, the DID estimate (0.249) is positive but statistically insignificant. These findings suggest that while digitalisation has played a role in increasing total factor productivity, its impact varies across enterprise types. The EST segment appears to have benefited the most, as evidenced by the statistically significant improvements in productivity. However, for OAEs and all enterprises, the effects are not highly witnessed.

Table 8 Impact of digitalisation on Total Factor productivity by Major activity

Estimated impact (coefficients)	Estimated Values (Average of Logs)		
	Manufacturing	Trade	Services
Before			
Low digitalised in 2016	-0.306	2.447	1.405
High digitalised in 2016	-0.088	3.02	1.613
Single difference in 2016	0.219 (0.213)	0.573 (0.522)	0.208 (0.109)
After			
Low digitalised in 2023	1.361	2.629	1.806
High digitalised in 2023	0.857	2.932	1.919
Single difference in 2023	-0.504 (0.604)	0.303*** (0.035)	0.113***(0.014)
Double difference	-0.723 (0.722)	-0.27 (0.522)	-0.095 (0.109)
Total observations	15248	24357	50264
R-square	0.25	0.07	0.15

*Source: Same as in Figure 1; Note: Robust Standard Error in Parenthesis; *P<0.1 **P<0.05 ***P<0.001*

Table 8 evaluates the effect of digitalisation on Total Factor Productivity (TFP) across manufacturing, trade, and services. The single difference estimates in 2016 is positive and statistically insignificant across all sectors.

Firms across all three sectors experienced a general increase in TFP by the year 2023. The single difference in 2023 shows varied results across sectors. The estimate for manufacturing is negative and statistically insignificant. However, for the trade and services estimates single difference estimates are statistically significant positive. The DID estimate is negative and insignificant across all three sectors. This suggest that relative advantage of highly digitalised firms over their low digitalised counterparts did not increase substantially over time.

Table 9 Impact of digitalisation on Labour productivity by Enterprise type

Estimated impact (coefficients)	Estimated Values (Average of Logs)		
	All enterprises	EST	OAE
Before			
Low digitalised in 2016	11.585	11.701	15.247
High digitalised in 2016	11.868	11.994	15.303
Single difference in 2016	0.283***(0.031)	0.293***(0.031)	0.055(0.293)
After			
Low digitalised in 2023	11.828	11.971	15.474
High digitalised in 2023	11.991	12.120	15.644
Single difference in 2023	0.163***(0.006)	0.149***(0.007)	0.169***(0.008)
Double difference	-0.12***(0.032)	-0.144	0.114(0.293)
Total observations	89870	35387	54483
R-square	0.25	0.17	0.31

*Source: Same as in Figure 1; Note: Robust Standard Error in Parenthesis; *P<0.1 **P<0.05 ***P<0.001*

Table 9 gives the estimates for the impact of digitalisation on labour productivity across different enterprise types. The single difference in pre COVID period is statistically significant for all Enterprises (0.283) and ESTs (0.293). However, in the OAEs. the estimated gap is statistically insignificant. By 2023, the single difference is statistically significant for all three enterprise types indicating high digitalised firms consistently outperformed their low digitalised counterparts in labour productivity in post COVID period.

The DID estimate is negative for all Enterprises (-0.12) and ESTs (-0.144). However, in the OAEs, the estimate (0.114) is positive but statistically insignificant. These findings suggest that digitalisation has positively influenced labour productivity across all enterprise types, though its impact varies. While high digitalised firms consistently maintain a productivity advantage over low digitalised firms, the narrowing of this gap over time, particularly among ESTs and all Enterprises.

Table 10 Impact of digitalisation on Labour productivity by Major activity

Estimated impact (coefficients)	Estimated Values (Average of Logs)		
	Manufacturing	Trade	Services
Before			
Low digitalised in 2016	11.684	12.081	11.266
High digitalised in 2016	11.997	12.274	11.538
Single difference in 2016	0.313***(0.079)	0.193(0.129)	0.272***(0.035)
After			
Low digitalised in 2023	12.049	12.044	11.443
High digitalised in 2023	12.203	12.239	11.595
Single difference in 2023	0.153***(0.016)	0.195***(0.012)	0.152***(0.007)
Double difference	-0.16**(0.80)	0.002(0.129)	-0.120***(0.036)
Total observations	15248	24357	50265
R-square	0.41	0.19	0.24

*Source: Same as in Figure 1; Note: Robust Standard Error in Parenthesis; *P<0.1 **P<0.05 ***P<0.001*

Table 10 assesses the impact of digitalisation on labour productivity across manufacturing, trade, and services. During pre-COVID period, the single difference is statistically significant in manufacturing (0.313) and services (0.272). However, in the trade sector it is statistically insignificant. In post COVID period, the first difference is statistically significant across all three sectors, with values of 0.153 in Manufacturing, 0.195 in Trade, and 0.152 in Services.

The double difference estimate, reveals sectoral variations. In manufacturing and services, the estimates (-0.16 and -0.120, respectively) are statistically significant and negative, indicating that the initial productivity advantage of high digitalised firms slightly diminished over time. This suggests that low digitalised firms may have gradually improved their digital adoption, reducing the gap. In contrast, the trade sector exhibited a near-zero double difference estimate (0.002), suggesting that the productivity gap between high and low digitalized firms remained stable over time in this sector. These findings highlight that digitalisation has positively influenced labour productivity across manufacturing, trade, and services, though its impact has varied by sector. While high digitalised firms have consistently maintained a productivity edge, the reduction in the productivity gap in manufacturing and services suggests that digital adoption is diffusing across firms in these sectors. However, the trade sector appears to have sustained a stable productivity gap, implying that digitalisation benefits may not have been as transformative in this industry.

6. Discussion and concluding remarks

This study signifies the role of digitalisation in enhancing financial inclusion and firm performance in the informal sector. By employing the Propensity Score Matching-Difference-in-Differences (PSM-DID) method, we establish that firms with high levels of digital adoption exhibit significantly improved financial inclusion and productivity outcomes compared to their counterparts. The results indicate that digital financial services, such as mobile banking, e-wallets, and online transactions, help bridge traditional gaps in financial access for informal enterprises. Additionally, firms leveraging digital technologies demonstrate increased total factor productivity (TFP) and labour productivity, reflecting the broader transformative potential of digitalisation in resource optimization and transaction cost reduction. However, the findings also highlight disparities in digital adoption and its benefits across different types of informal enterprises. Own-account enterprises (OAEs), particularly those with limited digital infrastructure or lower technological capabilities, face significant barriers in fully leveraging digitalisation. While some firms have successfully integrated digital tools into their operations, others struggle due to financial constraints, lack of digital literacy, or inadequate regulatory support. This uneven adoption suggests that a one-size-fits-all approach to digitalisation may not be effective, and targeted interventions are necessary to ensure equitable benefits across firms.

Moreover, the fadeout effect of digitalisation's impact underscores the importance of continuous innovation and adaptive strategies to sustain long-term benefits. Further, sectoral differences in digitalisation's impact require attention. While manufacturing and service sectors have witnessed narrowing productivity gaps due to digital adoption, the trade sector appears to have maintained a relatively stable productivity disparity. This suggests that digital tools may not be equally transformative across all industries, reinforcing the need for sector-specific digital policies to maximize benefits. Notably, while digitalisation initially provides a strong boost to financial inclusion and firm performance, the impact tends to fade out over time. The macroeconomic disruptions post-pandemic, such as inflationary pressures or reduced consumer demand, offset the potential gains from digitalisation. In sectors like informal manufacturing, digitalisation may have been more about survival during the pandemic than long-term transformation, leading to temporary rather than sustained productivity gains.

This diminishing effect could be attributed to saturation in technology adoption, lack of sustained innovation, or firms facing structural barriers that prevent continued improvements.

Without continuous adaptation and complementary policy measures, the initial gains from digitalisation may plateau, limiting its long-term effectiveness.

To ensure a more inclusive digital transformation, policymakers should prioritize expanding broadband connectivity, especially in underserved regions, to enable informal enterprises to integrate digital tools into their operations. Strengthening digital infrastructure can significantly enhance financial inclusion and productivity by reducing transaction costs and improving market access.

Our results indicate that high digitalised firms are more likely to access formal finance and higher productivity. There is an immediate need to targeted broadband expansion, particularly in informal sector enterprises, enabling digital adoption. Additionally, enhancing digital literacy through targeted training programs is essential to equip workers with the necessary skills to navigate digital financial services. Capacity-building initiatives should focus on empowering informal entrepreneurs with the knowledge to adopt and effectively use digital technologies. Financial incentives, such as tax breaks, subsidies, and technical assistance programs, should be provided to encourage digitalisation among informal enterprises. Supporting small and micro enterprises in their transition to digital platforms can accelerate the adoption of digital financial services and improve overall economic resilience. Furthermore, ensuring data protection and cybersecurity in digital transactions is crucial for fostering trust in digital financial services. Policymakers should develop clear guidelines and regulations that promote digital innovation while safeguarding businesses and consumers from potential risks. Addressing the digital divide requires an inclusive policy framework that considers the specific challenges faced by smaller informal firms. Public-private partnerships can play a pivotal role in bridging these gaps by developing accessible and affordable digital solutions tailored to the needs of informal sector enterprises.

7. Limitations and future research

While this study analyses the relationship between digitalisation, financial inclusion, and firm performance in informal manufacturing enterprises pre and post covid period, it faces several limitations. First, although a Difference-in-Differences (DID) framework is employed to identify causal impacts, the validity of the approach mainly based on the parallel trend's assumption. We have made efforts to test this assumption using low and high digitalised firms and parallel trends generally appear to hold. Productivity changes were shown across the different types of enterprises at varying levels of capital endowments in the low and high digitalised firms at pre and post covid period (refer Figure:4)

The construction of binary treatment variables based on whether a firm scores above the mean on a digitalisation or financial inclusion index introduces potential arbitrariness. While this approach facilitates comparability and ease of interpretation, it may mask important variation among firms that are marginally above or below the cutoff. Future work could consider more flexible specifications or use continuous treatment intensities to address this concern. Also, the study relies primarily on pseudo panel data constructed using cross-sectional firm-level data using PSM method. This restricts the ability to fully capture longer-term effects or evolving patterns of digitalisation.

The future research in these lines should explore the long-term impact of digitalisation on informal enterprises and investigate the role of complementary factors such as managerial capabilities, financial literacy, and regulatory frameworks in shaping digital adoption outcomes. A comprehensive approach that integrates digital infrastructure, skill development, and supportive policies will be key to fostering an inclusive and resilient digital economy for the informal sector.

Dr. K. Chandra Shekar is Assistant professor at Centre for Development Studies (CDS), Thiruvananthapuram. His areas of research are Economics of Innovations, Innovation in Developing countries, Informal Economy, MSMEs, Industry and Economic Development. He could be reached at chandrashekar@cds.edu

Ms. K. Vidyarani is a Doctoral Scholar at the Centre for Development Studies, Thiruvananthapuram. She is working on the topic titled 'Credit availability and the performance of MSMEs in India'. She could be reached at vidyaranikvidyarani@gmail.com

References

- Abadie, A., & Imbens, G. W. (2006). Large sample properties of matching estimators for average treatment effects. *econometrica*, *74*(1), 235–267. https://doi.org/10.1111/j.1468-0262.2006.00655.x

- Abor, J. Y., Issahaku, H., Amidu, M., & Murinde, V. (2020). Financial inclusion and economic growth 1. In *Contemporary issues in development finance* (pp. 263-286). Routledge. https://doi.org/10.4324/9780429450952
- Adamides, E., & Karacapilidis, N. (2020). Information technology for supporting the development and maintenance of open innovation capabilities. *Journal of Innovation & Knowledge*, *5*(1), 29-38. https://doi.org/10.1016/j.jik.2018.07.001
- Barney, J., Wright, M., & Ketchen Jr, D. J. (2001). The resource-based view of the firm: Ten years after 1991. Journal of management, 27(6), 625-641. https://doi.org/10.1177/014920630102700601
- Basu, K., 2019. Country studies: india. In: Nayyar, D. (Ed.), Asian transformations: An Inquiry into the Development of Nations. Oxford University Press, pp. 401–420.
- Basu, S., Fernald, J. G., Oulton, N., & Srinivasan, S. (2003). The case of the missing productivity growth, or does information technology explain why productivity accelerated in the United States but not in the United Kingdom? *NBER macroeconomics annual*, *18*, 9-63.
- Bayo-Moriones, A., Billón, M., & Lera-López, F. (2013). Perceived performance effects of ICT in manufacturing SMEs. *Industrial Management & Data Systems*, *113*(1), 117-135. https://doi.org/10.1108/02635571311289700
- Benjamin, R., & Wigand, R. (1995). Electronic markets and virtual value chains on the information superhighway. *MIT Sloan Management Review*.
- Berndt, E. R., Morrison, C. J., & Rosenblum, L. (1992). High-tech capital formation and labor composition in US manufacturing industries: an exploratory analysis.
- Bhalla, S. (2009). Definitional and Statistical Issues Relating to Workers in Informal Employment, New Delhi: National Commission for Enterprises in the Unorganised Sector, Government of India.

- Bharadwaj, A. S. (2000). A resource-based perspective on information technology capability and firm performance: an empirical investigation. *MIS quarterly*, 169-196. https://doi.org/10.2307/3250983

- Bharadwaj, A. S. (2000). A resource-based perspective on information technology capability and firm performance: an empirical investigation. *MIS quarterly*, 169-196. https://doi.org/10.2307/3250983

- Bhattacharjee, B., Kumar, S., Verma, P., & Maiti, M. (2024). Determinants of digitalization in unorganized localized neighborhood retail outlets in India. *Journal of Theoretical and Applied Electronic Commerce Research*, *19*(3), 1699-1716.
- Biagi, F. (2013). *ICT and Productivity: A Review of the Literature* (No. 2013/09). Institute for Prospective Technological Studies Digital Economy Working Paper.
- Bresnahan, T. F., & Trajtenberg, M. (1995). General purpose technologies 'Engines of growth'? *Journal of econometrics*, *65*(1), 83-108. https://doi.org/10.1016/0304-4076(94)01598-T
- Brynjolfsson, E. (1993). The productivity paradox of information technology. *Communications of the ACM*, *36*(12), 66-77.
- Brynjolfsson, E., Hitt, L. M., & Yang, S. (2002). Intangible assets: Computers and organizational capital. *Brookings papers on economic activity*, *2002*(1), 137-181.
- Calvino, F., Criscuolo, C., & Ughi, A. (2024). Digital adoption during COVID-19. *Documents de travail de l'OCDE sur la science, la technologie et l'industrie*.
- Carr, N. G. (2003). IT doesn't matter. *Educause Review*, *38*, 24-38.
- Chen, M. A (2007). *Rethinking the Informal Economy: Linkages with the Formal Economy and the Formal Regulatory Environment,* DESA Working Paper No. 46. UN Department of Economic and Social Affairs.
- Chen, M. A., Grapsa, E., Ismail, G., Rogan, M., Valdivia, M., Alfers, L., ... & Roever, S. (2022). COVID-19 and informal work: Evidence from 11 cities. *International Labour Review*, *161*(1), 29-58.
- Curran, D. (2018). Risk, innovation, and democracy in the digital economy. *European journal of social theory*, *21*(2), 207-226. https://doi.org/10.1177/1368431017710907
- Deaton, A. (1985). Panel data from time series of cross-sections. *Journal of econometrics*, *30*(1-2), 109-126. https://doi.org/10.1016/0304-4076(85)90134-4

- Demirguc-Kunt, A., Klapper, L., Singer, D., Ansar, S., & Hess, J. (2018). *The Global Findex Database 2017: Measuring financial inclusion and the fintech revolution*. World Bank Publications. Retrieved from https://globalfindex.worldbank.org
- Dewan, S., & Kraemer, K. L. (2000). Information technology and productivity: Evidence from country-level data. *Management science*, *46*(4), 548-562. https://doi.org/10.1287/mnsc.46.4.548.12057
- Dutta, N., & Kar, S. (2022). *Lockdown and Rural Joblessness in India: Gender Inequality in Employment?* (No. 15270). IZA Discussion Papers.
- Dutta, N., Kar, S., & Guha, S. (2023). Informal sector in India and adoption of digital technologies. *Indian Growth and Development Review*, *16*(3), 230-246.
- Erkmen, T., Günsel, A., & Altındağ, E. (2020). The role of innovative climate in the relationship between sustainable IT capability and firm performance. *Sustainability*, *12*(10), 4058.
- Erumban, A. A., & Das, D. K. (2020). ICT investment and economic growth in India: An industry perspective. *Digitalisation and Development: Issues for India and Beyond*, 89-117. https://doi.org/10.1007/978-981-13-9996-1_3
- Fernández-Portillo, A., Almodóvar-González, M., & Hernández-Mogollón, R. (2020). Impact of ICT development on economic growth. A study of OECD European union countries. *Technology in Society*, *63*, 101420. https://doi.org/10.1016/j.techsoc.2020.101420
- Ferreira, J. J., Fernandes, C. I., & Ferreira, F. A. (2019). To be or not to be digital, that is the question: Firm innovation and performance. *Journal of Business research*, *101*, 583-590. https://doi.org/10.1016/j.jbusres.2018.11.013
- Gebauer, H., Fleisch, E., Lamprecht, C., & Wortmann, F. (2020). Growth paths for overcoming the digitalization paradox. *Business Horizons*, *63*(3), 313-323. https://doi.org/10.1016/j.bushor.2020.01.005
- Gertler, P. J., Martinez, S., Premand, P., Rawlings, L. B., & Vermeersch, C. M. (2011). *Impact evaluation in practice*. World Bank Publications.
- Goldar, B. (2020). Services input and productivity in Indian manufacturing plants. Indian Growth and Development Review, 13 (1): 99-124. https://doi.org/10.1108/IGDR-11-2018-0117.

- Goldar, B. (2024). Total Factor Productivity Growth in India Manufacturing in the Post-Reform Period. *Available at SSRN 4681660*.
- Gordon, R. J. (2000). Does the "new economy" measure up to the great inventions of the past? *Journal of economic perspectives*, *14*(4), 49-74.
- Guo, X., Li, M., Wang, Y., & Mardani, A. (2023). Does digital transformation improve the firm's performance? From the perspective of digitalization paradox and managerial myopia. *Journal of Business Research*, *163*, 113868. https://doi.org/10.1016/j.jbusres.2023.113868
- ILO (2020). Keys for effective teleworking during the COVID-19 pandemic. Online available athttps://www.ilo.org/global/about heilo/newsroom/news/WCMS_739879/lang..en/index.htm.
- Joseph, K. J. & Abraham, V. (2007). Information technology and productivity: Evidence from India's manufacturing sector. Working Paper 389, Centre for Development Studies, Thiruvananthapuram, Kerala, India.
- Karanja, E. and Waiganjo, E.W. (2020), "Digital transformation and its impact on organizational decision making: a systematic review of the literature", Journal of Management and Strategy, Vol. 11 No. 1, pp. 1-14.
- Krishna, K. L., Goldar, B., Aggarwal, S. C., Das, D. K., Erumban, A. A. and Das, P. C. (2018). Productivity Growth and Levels - A comparison of Formal and Informal Manufacturing in India, Working Paper No.291, Centre for Development Economics, Delhi School of Economics, Delhi.
- Krishna, K.L., Goldar, B., Das, D. K., Aggarwal, S. C., Erumban, A. A. & Das, P. C. (2020). Manufacturing productivity in India: the role of foreign sourcing of inputs and domestic capacity building. In B. M. Fraumeni (ed.), Measuring Economic Growth and Productivity: Foundations, KLEMS Production Models, and Extensions (pp. 95-116), Academic Press.
- La Porta, R., & Shleifer, A. (2014). Informality and development. Journal of economic perspectives, 28(3), 109-126.
- Li, H., Wu, Y., Cao, D., & Wang, Y. (2021). Organizational mindfulness towards digital transformation as a prerequisite of information processing capability to achieve market agility. *Journal of Business research*, *122*, 700-712. https://doi.org/10.1016/j.jbusres.2019.10.036

- Ministry of Statistics and Programme Implementation (MoSPI) (2015). Statistical Yearbook of India. https://164.100.161.63/sites/default/files/Statistical_year_book_india_chapters/INFORMATION_TECHNOLOGY.pdf
- Mithas, S., & Rust, R. T. (2016). How information technology strategy and investments influence firm performance. *Mis Quarterly*, *40*(1), 223-246. https://www.jstor.org/stable/26628391
- Mitra, A., Sharma, C. & Véganzonès-Varoudakis, M-A. (2016). Infrastructure, ICT and Firms' Productivity and Efficiency: An Application to the Indian Manufacturing. In F. De Beule and K. Narayanan (eds.), Globalization in Indian Industries: Productivity, Exports and Investment (pp. 17-41), Springer.
- Mukherjee, D. (2016). Informal economy in emerging economies: not a substitute but a complement! *International Journal of Business and Economic Development (IJBED)*, *4*(3).
- Nambisan, S. (2017). Digital entrepreneurship: Toward a digital technology perspective of entrepreneurship. *Entrepreneurship theory and practice*, *41*(6), 1029-1055. https://doi.org/10.1111/etap.12254
- Nambisan, S., Wright, M., & Feldman, M. (2019). The digital transformation of innovation and entrepreneurship: Progress, challenges and key themes. *Research policy*, *48*(8), 103773. https://doi.org/10.1016/j.respol.2019.03.018
- NCEUS. (2007). *Report on conditions of work and promotion of livelihoods in the unorganised sector*. National Commission for Enterprises in the Unorganised Sector.
- NSSO (2016): "Unincorporated Non-Agricultural Enterprises (Excluding Construction) in India as on July 2015–June 2016", Ministry of Statistics and programme implementation, National Sample Survey Organisation, Government of India.
- NSSO (2023): "Annual Survey of Unincorporated Sector Enterprises (ASUSE) in India as on October 2022 – September 2023", Ministry of Statistics and programme implementation, National Sample Survey Organisation, Government of India.
- OECD (2020), OECD Economic Outlook, Interim Report March 2020, OECD Publishing.
- Ozili, P. K. (2018). Impact of digital finance on financial inclusion and stability. *Borsa istanbul review*, *18*(4), 329-340. https://doi.org/10.1016/j.bir.2017.12.003

- Ozili, P. K., & Syed, A. A. (2024). Financial inclusion and fintech research in India: A Review. *Decentralized Finance and Tokenization in FinTech*, 77-94.
- Polák, P. (2017). The productivity paradox: A meta-analysis. *Information Economics and Policy*, *38*, 38-54. https://doi.org/10.1016/j.infoecopol.2016.11.003
- Reddy, K., & Sasidharan, S. (2024). *Digitalization, firm performance, and internationalization of micro firms in India* (ADB Background paper). Asian Development Bank. https://www.adb.org/sites/default/files/institutional-document/1052731/adpr2025bp-digitalization-performance-micro-firms-india.pdf
- Rosenbaum, P. R. (2002). Observational studies. New York: Springer-Verlag.
- Sandulli, F. D., Baker, P. M., & López-Sánchez, J. I. (2014). Jobs mismatch and productivity impact of information technology. *The Service Industries Journal*, *34*(13), 1060-1074. https://doi.org/10.1080/02642069.2014.939638
- Sanga, B., & Aziakpono, M. (2023). FinTech and SMEs financing: A systematic literature review and bibliometric analysis. *Digital Business*, *3*(2), 100067. https://doi.org/10.1016/j.digbus.2023.100067
- Seconded European Standardization Expert for India (2021). Indian ICT Sector Profile Report https://sesei.eu/wp-content/uploads/2023/03/Indian-ICT-Sector-Report_Nov-2021_Final-1.pdf
- Senyo, P. K., Gozman, D., Karanasios, S., Dacre, N., & Baba, M. (2023). Moving Away from Trading on the Margins: Economic Empowerment of Informal Businesses through FinTech. *Information Systems Journal*, 33(1), 154-184. https://doi.org/10.1111/isj.12403
- Sheikh, A. A., Glavee-Geo, R., Karjaluoto, H., & Hinson, R. E. (2023). Mobile Money as a Driver of Digital Financial Inclusion. *Technological Forecasting and Social Change*, 186, https://doi.org/10.1016/j.techfore.2022.122158
- Shekar, K. C. and K. Mansoor. 2021. COVID-19: Lockdown Impact on Informal Sector in India, University Practice Connect, Azim Premji University, COVID-19: Lockdown Impact on Informal Sector in India – University Practice Connect (azimpremjiuniversity.edu.in)
- Shekar, K.C., & Joseph, K.J., Beena P.L., (2023) innovations and firm performance informal manufacturing enterprises. Economic and Political Economy weekly, 58(30)
- Shekar, K.C. and Nataraj, M. (2023), "Subcontracting and enterprise development in India's informal manufacturing sector", *Journal of Small Business and Enterprise*

Development, Vol. 30 No. 3, pp. 448-474. https://doi.org/10.1108/JSBED-02-2022-0106

- Smith, J. and Johnson, A. (2023), "digital transformation: catalyst for innovation in products and services", Journal of Business Innovation, Vol. 15 No. 2, pp. 123-145.
- Smith, R. and Davis, L. (2022), "Optimizing product positioning: a data-driven approach", Journal of Marketing Research, Vol. 9 No. 4, pp. 321-345.
- Solow, R. (1987). We'd better watch out. *New York Times Book Review*, *36*.
- Stone, C. A., & Tang, Y. (2019). Comparing Propensity Score Methods in Balancing Covariates and Recovering Impact in Small Sample Educational Program Evaluations. *Practical Assessment, Research, and Evaluation*, 18(1), 13.
- Telecom Regulatory Authority of India (2024). "Indian Telecom Service Indicator Report" for the Quarter April-June, 2024. https://pib.gov.in/PressReleasePage.aspx?PRID=2063567
- Tranos, E. (2012). The causal effect of the internet infrastructure on the economic development of European city regions. *Spatial Economic Analysis*, *7*(3), 319-337. https://doi.org/10.1080/17421772.2012.694140
- Yunis, M., Tarhini, A., & Kassar, A. (2018). The role of ICT and innovation in enhancing organizational performance: The catalysing effect of corporate entrepreneurship. *Journal of Business Research*, *88*, 344-356. https://doi.org/10.1016/j.jbusres.2017.12.030

Appendix

Table A1: Cobb Douglas Production function

Log output(Q)	Coef.	St. Err.	t-value	p-value	[95% Conf	Interval]	Sig
Log capital(K)	.179	.001	245.57	0.000	.178	.181	***
Log Labour (L)	.998	.002	598.13	0.000	.995	1.001	***
Constant	9.254	.008	1141.8	0.000	9.238	9.27	***

Mean dependent var	11.838	SD dependent var	1.245
R-squared	0.482	Number of obs	722805
F-test	336346.033	Prob > F	0.000
Akaike crit. (AIC)	1892694.496	Bayesian crit. (BIC)	1892728.969

*** *p<.01*, ** *p<.05*, * *p<.1*

Table A2 Variable description

Name	Definition
Digitalisation index	Summation index of Internet, web presence, intranet, sell online, purchase online, narrowband, fixed broadband, mobile broadband, Lan, extranet, email, telephonic internet, Information online, Getting online government service, Information from general government organizations, Internet banking, online financial services, online customer services, online delivery, online recruitment, online training
Digitalisation Dummy	Categorical variable, 0=Low digitalisation; 1=High digitalisation
Financial inclusion index	Summation index of central and state level lending institutions, government, commercial banks-operative banks and societies, micro finance institutions, other institutional agencies and those firms which have bank account
Total factor productivity	Continuous variable (log)
Labour productivity	Continuous variable calculated by dividing output (GVA) by total number of workers
Home enterprises	Dummy variable, 1 if enterprises is located within household "0" otherwise
Gender	Dummy variable, "1" if it is female owner and "0" otherwise
Sector	Categorical variable, 1 = Rural 2 = Urban
Social group	Categorical variable, 1= SC/STs, 2=OBC 3= General category
Enterprise type	Dummy variable, 1 if enterprise is OAE and 0 if it is EST
Subcontract	Dummy variable, 1 if firm has subcontract 0 firm not subcontracted
Accounts maintained	Dummy variable, 1 if firm is registered 0 if it is not registered
Age of the firm	Continuous variable
Capital value	Continuous variable

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Centre for Development Studies
Prasanth Nagar, Ulloor,
Thiruvananthapuram 695 011
Kerala, India
Phone: +91 471 2774200
Website: www.cds.edu

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