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ARTÍCULO

Firm-level digital technology and Total Factor Productivity in a developing country: Evidence from panel data in Vietnam

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Abstract: In the era of the digital economy, the relationship between digital transformation and total factor productivity at the firm level has incalculable repercussions for businesses seeking to sustain high-quality growth. In addition, it is crucial to increase the total factor productivity of a company because it contributes to the accomplishment of sustainable development. Consequently, this paper investigates the effects of firm-level digital technology on Total Factor Productivity (TFP) levels using Vietnamese small and medium-sized enterprises (SMEs) data from 2015 to 2019. Using an analytical framework, the research tests the learning-by-doing hypothesis. The study categorizes Firm-level digital technology as follows: (1) Computer-operated devices, (2) Personal computers without Internet access, and (3) Personal computers with Internet access. After controlling for probable endogeneity, our empirical findings demonstrate that digital technology positively affects firm productivity. However, the digital technology productivity premium varies across businesses.

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1. Introduction

Over the past decade, there has been a notable increase in economic growth attributed to the expansion of the digital economy. The digital economy scale of 47 prominent nations reached a pinnacle of 38.1 trillion US dollars in the year 2021. This indicates that the growth rate has been increasing at 15.6% annually. The United States and the European Union have both increasingly turned to advanced technologies to foster the growth of the digital economy on a global scale. The development of the digital economy has prompted firms to recognize the trend and undergo digital transformation by adopting novel technologies. In the context of the emergence of the digital economy and the resulting significant changes in technology and the market environment, many organizations are opting to utilize digital tools and platforms to monitor organizational change and integrate innovation into their business processes, thereby contributing to endogenous growth in the country's economy (Ren et al., 2022a; Sadiq et al., 2023). It is imperative to acknowledge that the enhancement of productivity in various industries plays a pivotal role in promoting sustained economic growth and serves as a fundamental component of the process of industrialization (Acemoglu and Zilibotti, 2001; Barro and Sala-i-Martin, 1995; Diewert, 2014; El-hadj and Brada, 2009). Enhancing productivity in the digital economy has emerged as a crucial driver of economic progress, as evidenced by scholarly works such as Nakatani (2021) and Sadiq et al. (2022a). The correlation between innovation and productivity during the digital age is becoming a crucial inquiry among scholars, as evidenced by the works of Brynjolfsson et al. (2008) and Gal, Nicoletti, von Rüden, OECD, and Renault (2019). The scholarly literature, both theoretical and empirical, presents compelling evidence that the adoption of digital technologies is likely to yield significant productivity gains (Brynjolfsson et al., 2008; Syverson, 2011). Nonetheless, the industry and firm levels have presented a more nuanced perspective based on empirical evidence (Acemoglu et al., 2014; E. Bartelsman et al., 2017; Cette et al.. 2017).

According to scholarly sources such as Ana et al. (2020) and Goldfarb and Tucker (2019), implementing digital business solutions such as email, website creation, and computer technology can yield significant advantages, particularly for business enterprises. Online business tools can effectively decrease production expenses, expand potential business prospects, and augment profitability. The available literature regarding the influence of digital technology implementation on productivity is notably limited, particularly in the context of developing nations. Furthermore, the scarcity of research that seeks to measure these effects through utilizing data at the organizational level is even more pronounced. This study addresses the deficiencies mentioned above in the existing body of literature.

Simultaneously, existing cross-country data regarding the implementation of digital technologies at the firm level indicates that the distribution of adoption among firms is extensive and varies considerably across nations. This is evidenced by studies conducted by Hagsten et al. (2013), DeStefano et al. (2017b), and DeStefano et al. (2018). The dispersion mentioned in Andrews et al.' (2018) study is linked to hindrances in adoption contingent upon varying capabilities and incentives among firms, industries, and countries. Consequently, conducting further research on a particular nation could provide policymakers with additional empirical data to make informed decisions. A limited body of research examines the distinctions between companies that have undergone digital transformation and those that have not. Empirical evidence suggests a strong association between digital economy-related activities and total factor productivity (TFP).

Nevertheless, the causal relationship between digital technology-related actions and firms' productivity remains ambiguous. Specifically, it is uncertain whether firms become more productive through learning by doing or if productive firms tend to adopt digital-related technologies, as posited by Bernard and Jensen (1999), Melitz (2003), Wagner (2007), and Ngo and Nguyen (2019). The present investigation aims to examine the validity of the learning-by-doing hypothesis.

The manufacturing industry holds a pervasive presence in Vietnam and plays a crucial role in the process of industrialization. According to Ngo and Tran's (2020) findings, the manufacturing sector's relative contribution to the national economy has steadily increased. According to estimates, the manufacturing sector constitutes 15% of Vietnam's workforce and is anticipated to generate a substantial number of employment opportunities in the country during the forthcoming decade. Moreover, this will probably facilitate the process of structural transformation and industrialization. The existing body of literature about Vietnam exhibits a dearth of empirical support for the Total Factor Productivity (TFP) disparity between digitalized and non-digitalized manufacturing enterprises, particularly from the standpoint of Small and Medium-sized Enterprises (SMEs). This knowledge gap is a significant hindrance to achieving industrialization in Vietnam.

The primary aims of this study are twofold: firstly, to assess the total factor productivity (TFP) of small and medium-sized enterprises (SMEs) operating in the manufacturing sectors of Vietnam between 2015 and 2019, and secondly, to investigate any disparities in TFP levels between SMEs that have undergone digitalization and those that have not, over the same period. The present study's research inquiries encompass the following: (1) What is the magnitude of TFP exhibited by small and medium-sized enterprises operating in the manufacturing industry of Vietnam between 2015 and 2019? To what extent do the total factor productivity (TFP) levels vary between small and medium-sized enterprises (SMEs) that have undergone digitalization and those that have not during the period spanning from 2015 to 2019?

Our study contributes to the existing body of literature in several respects. Initially, we examine the Total Factor Productivity (TFP) of Small and Medium Enterprises (SMEs) in the manufacturing sector of Vietnam, with a focus on its contemporary progress. This study contributes to the extant body of literature by examining the disparities in total factor productivity (TFP) between small and medium-sized enterprises (SMEs) that have undergone digitalization and those that have not, utilizing novel and current survey data obtained from the Vietnamese General Statistical Office at the firm level. Thirdly, the implications drawn from Vietnam's experience could serve as a valuable lesson for transitioning nations facing comparable circumstances.

The present manuscript is organized in the following manner. The second section of the paper comprises a literature review that provides an overview of digitalization from the perspective of firms. It also examines the relationship between digital technology and total factor productivity (TFP) at the firm level and proposes an analytical framework. The third section of the document outlines the dataset and the econometric techniques employed. Section 4 pertains to the presentation of empirical findings. The fifth section provides a concise overview of the research outcomes and suggests potential policy implications and avenues for future research.

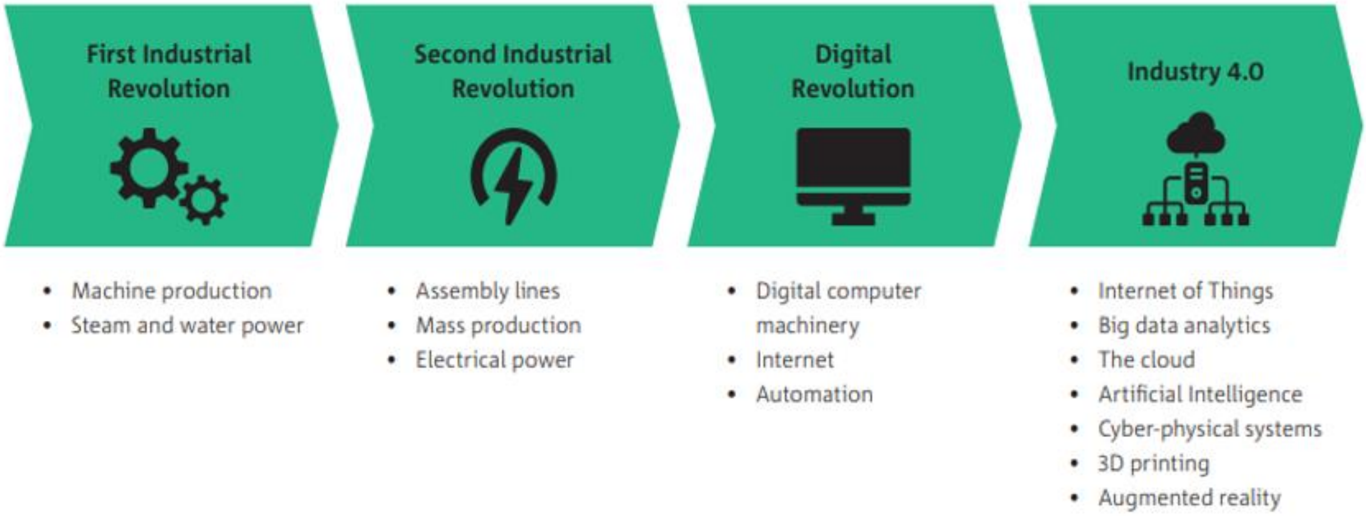
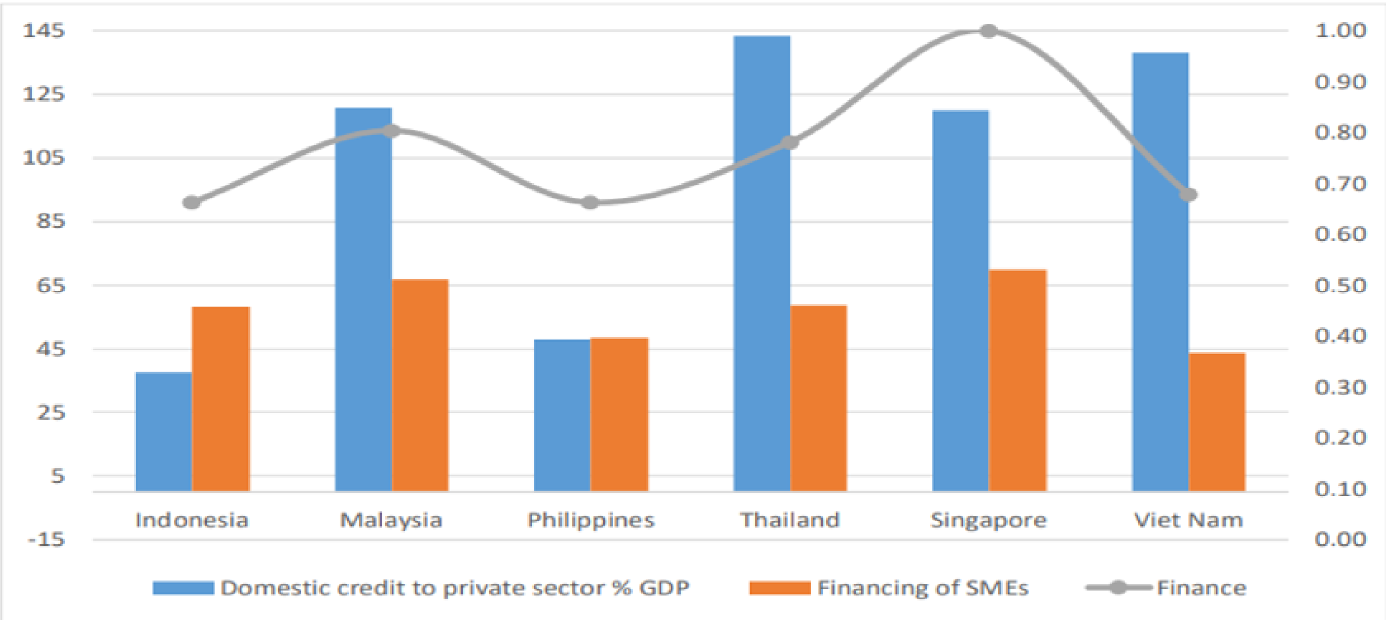


Figure 1. Stages of the Industrial Revolution



GDP = gross domestic product, SMEs = small and medium-sized enterprises.
Sources: World Bank and World Economic Forum.

Figure 2. Financial support of the banking system for businesses (2019)

2. Literature Review

Contemporary research has extensively examined the possible definition of digitalization. Nonetheless, due to divergent perspectives, a consensus on the concept has not been achieved, owing to the presence of equivocal viewpoints. Notably, the definitions provided by Sadiq et al. (2022b) and Vial (2019) shed light on the crucial facets of digital transformation. As per Frank et al. (2019), digital transformation refers to using digital technologies to improve overall business operations, including streamlining existing processes, enhancing customer services, and developing novel business models. This ultimately enhances the overall performance and competitive advantage of the firm. Agarwal et al. (2010) define digital transformation as the systematic measurement and analysis of technical information and its utilization. According to Fitzgerald et al. (2014), digitalization is a state-of-the-art tool to achieve business benefits. According to scholarly discourse, Piccinini et al. (2015) and Majchrzak et al. (2016) have expressed comparable perspectives. According to the studies conducted by Matt et al. (2015) and Tabrizi et al. (2019), the fundamental concept of digitalization is to facilitate strategic transformation.

In summary, it can be posited that digitalization encompasses the integration of enterprise, technology, and data, resulting in a competitive edge and value creation for businesses (Ren et al., 2022b). Likewise, certain academics have evaluated the phenomenon using a solitary proxy when discussing its measures. However, this approach is not congruent with the attributes of digitization. Academic researchers have demonstrated a significant level of interest in examining the efficacy of this phenomenon concerning fostering business growth and development, as evidenced by the works of Hadjielias et al. (2021) and Yi et al. (2021). The current investigation, however, focuses on the efficacy of the intervention in the overall factor productivity of companies.

3. Digitalization from Firm-Level Perspectives

The proliferation of Information and Communication Technology (ICT) has been identified as a significant catalyst for micro-level structural transformations, including the transition in the employment composition from low to high skills and the reconfiguration of a company's workplace organization Arendt and Grabowski (2017); Hollenstein and Stucki (2012). It is commonly assumed that heightened information and communication technology (ICT) usage will ultimately lead to increased labor and total factor productivity (TFP).

Redistributing employment and capital among firms is crucial in determining structural transformation and overall productivity growth. This phenomenon is often accompanied by the entry and exit of firms, as noted by various scholars such as Caves (1998), E. J. Bartelsman and Doms (2000), Krüger (2008), and Dosi and Nelson (2010). The utilization of novel technologies and innovation are the primary drivers behind this process of resource redistribution. The study by Dachs et al. (2017) examines the reallocation of employment gains and losses from innovation. The study's findings indicate that the magnitude of employment gains and losses positively correlates with technology intensity in the sector. The impact of innovation on employment is most pronounced in high-technology manufacturing, followed by knowledge-intensive services, low-technology manufacturing, and less knowledge-intensive services. In general, invention has a predominantly favorable impact on employment growth. However, there are certain instances where this trend is not observed, specifically in manufacturing sectors during times of economic downturn.

The digital economy is primarily defined in terms of the Internet and related information and communications technologies (ICT) by Barefoot et al. (2018) and other scholars. According to Dahlman et al. (2016), the digital economy is founded on digital technologies, information networks, and the various activities individuals engage in over these networks. The digital economy is a concept that lacks a universally accepted definition. However, it can be understood as comprising three main components. Firstly, the digital-enabling infrastructure, which encompasses computer hardware, software, telecommunications equipment and services, structures, the Internet of Things (IoT), and support services, is necessary for a computer network to exist and operate. Secondly, the digital transactions that take place using this system, commonly referred to as "e-commerce," include business-to-business (B2B) e-commerce, business-to-consumer (B2C) e-commerce, and peer-to-peer (P2P) e-commerce. Finally, digital economy users create and access content, known as "digital media," including direct sale digital media, free digital media, and big data. The intricate and extensive nature of the digital economy poses a challenge in implementing the concept in developing nations, particularly when viewed from the standpoint of firms. This paper adopts an innovation perspective to examine the digital economy at the firm level. Specifically, we investigate digital economy firms about digital technologies, drawing on the works of Haller and Siedschlag (2011), Ana et al. (2020), Gal et al. (2019), and Brambilla (2018).

4. Firm-Level Digital Technology and TFP

Numerous studies conducted at the firm and industry levels have demonstrated a positive correlation between investment in digital technologies and productivity performance. These studies include works by Dewan and Min (1997), Dedrick et al. (2003), Hollenstein (2004), Draca et al. (2007), Syverson (2011), Arendt and Grabowski (2017), Gal et al. (2019), and Ana et al. (2020). According to Dewan and Min's (1997) research, investing in information technology is a replacement for traditional capital and can potentially improve labour efficiency. In his study, Hollenstein (2004) analyzes the determinants of firms' Information and Communication Technologies (ICT) adoption, utilizing data from Swiss firms. The author finds that various adoption variables, such as the timing of adoption of specific ICT elements and the degree of ICT usage, hold significant importance. Arendt and Grabowski (2017) have established a correlation between innovation outputs and ICT and productivity gains by utilizing micro-level data from 1,000 Polish companies, employing the CDM approach and the new firm paradigm. The research has verified the intermediary function of innovations and information and communication technology (ICT) complementarities in enhancing productivity.

The study conducted by Doms et al. (2004) examines the correlation between investments made in information technology (IT) and the performance of the retail industry. The authors' study reveals that most retail IT investment, employment, and establishment growth are attributed to large firms. Furthermore, the authors establish a significant correlation between IT investment intensity and productivity growth.

The nature of the relationship is diverse. According to Nakatani's (2021) research, there is a positive correlation between the size or age of a firm and its total factor productivity growth, with larger or younger firms exhibiting higher growth rates than their counterparts. Additionally, the study reveals that economies of scale are more pronounced in the ICT service industry than in the ICT manufacturing sector.

According to Ana et al. (2020), adopting email and website technologies is associated with a probability-adjusted median (log) revenue-based total factor productivity premium of 1.6 percent and 2.2 percent, respectively. Notably, the premium for website adoption is higher than those associated with exporting and managerial experience. Digital technologies facilitate innovation for firms, such as enhancing business processes and automating routine tasks. According to various studies (Bartel et al., 2007; Brynjolfsson et al., 2008; Akerman et al. (2013), the employment of such technologies has the potential to decrease expenses associated with engaging with suppliers and customers.

Borowiecki et al. (2021) conducted a recent study that examines the impact of intangibles and digital adoption on firm-level productivity in the Netherlands. The findings of the study indicate that there are significant productivity benefits associated with intangibles and digital adoption. The outcomes exhibit heterogeneity across various sectors and scales of firms. The findings suggest that intangible assets, quantified by the degree of digital proficiency, exert a favorable and statistically noteworthy influence on the expansion of productivity at the organizational level within the service industry and among nascent enterprises. The significance of software investment in enhancing productivity is crucial for firms with low productivity levels. The discoveries above underscore the possibility of intangible assets aiding in improving productivity for underperforming businesses. The evidence indicates positive and significant productivity benefits associated with ICT hardware and high-speed broadband investments. The study conducted by Nakatani (2021) makes a valuable contribution to the existing literature by highlighting that large and young firms tend to exhibit greater growth in total factor productivity than their counterparts. This conclusion is based on an analysis of cross-country firm-level data. The ICT service sector shows a greater manifestation of economies of scale than the ICT manufacturing sector.

Nevertheless, certain research studies present a contrasting perspective on the favorable impact of digital technology on productivity. Acemoglu and colleagues (2014) conducted a survey which indicated that, in general, the IT intensity had no significant impact on productivity in the US manufacturing sector. However, their findings did reveal a notable exception in the computer-producing industry from 1977 through 2007. According to the research conducted by E. Bartelsman and colleagues in 2017, there is no statistically significant impact of broadband access on the productivity of firms in European nations. DeStefano and colleagues (2018) discovered that firm productivity remains unaffected by broadband ADSL, based on their analysis of UK data from the early 2000s.

The presence of conflicting empirical data indicates the "productivity paradox," a term coined by Robert Solow in 1987 to describe the phenomenon of the apparent lack of productivity growth during the 1970s and 1980s, despite the rapid advancement of information technologies. Furthermore, current developments are occurring within the digital economy realm.

Various explanations have been put forth globally. According to certain authors, the impact of digital technologies on productivity is temporary and will not significantly alter living standards in the long run. Grabska et al. (2017) propose that the deceleration in productivity observed in the Netherlands could be attributed to a reversion to the mean following a period of robust productivity expansion facilitated by the ICT revolution from 1995 to 2004. The findings are consistent with Gordon's (2012) forecast that digital technologies will have a comparatively lesser impact on society than preceding technological advancements.

Several scholars have highlighted the unexplored possibilities of digital technologies and have contended that the current deceleration in productivity reflects a phase of transformation during which certain companies still acquire proficiency in their utilization. According to Andrews et al.'s (2016) findings, the deceleration of aggregate productivity can be attributed to the diminished productivity growth of lagging firms, except for the top 5% of firms that exhibit the highest productivity, also known as frontier firms. In contrast, numerous OECD economies have displayed robust productivity growth among frontier firms, indicating less effective dissemination of technology from the top-performing entities to the remaining ones. According to van Heuvelen and Bettendorf's (2018) study, there is no evidence of productivity divergence in the Netherlands. However, the study does indicate that the productivity frontier is marked by robust entry and exit. The comprehensive analysis of entry and exit dynamics suggests that the diffusion of technology facilitates the convergence of the productivity levels of the most efficient firms towards the productivity frontier.

However, recent findings from developed nations offer a reason for hope. Gal et al. (2019) conducted a study to investigate the impact of digital technologies on firms' productivity. The study employs cross-country firm-level data from 20 European Union nations and Turkey to examine productivity and industry-level data on digital technology adoption within an empirical framework that considers firm heterogeneity. The findings indicate that implementing digital technologies within a given industry positively impacts the productivity gains experienced by firms operating within that industry.

Previous literature reviews conducted by Syverson (2011) and Draca et al. (2007) have established a significant and affirmative correlation between Information and Communication Technology (ICT) and productivity. In contrast to the recent evidence presented by DeStefano et al. (2017a) for the United Kingdom, the findings suggest that ICT does not lead to increased productivity. However, it may increase in firm size as measured by sales or employment.

Hjort and Poulsen (2019) have discovered affirmative impacts of the Internet's introduction on the productivity of firms in Africa, despite the limited availability of evidence for developing nations. According to a study conducted by the World Bank on Argentina, Brazil, Chile, Colombia, and Mexico, implementing digital technology provides more efficient avenues for productivity (Dutz et al., 2018). The investigation reveals that the overall productivity of companies implementing technology has risen in all the countries where data was accessible. The study conducted in Argentina was based on labor productivity and was carried out by Brambilla and Tortarolo (2018), Iacovone and Pereira Lopez (2018), Almeida et al. (2017), and Dutz, Mation et al. (2017).

Cross-national investigations into the implementation of digital technologies at the level of individual firms indicate that such adoption is widespread and displays notable variation across different countries (Hagsten et al., 2013). According to Peña-López's (2017) research, the prevalence of cloud computing adoption is more than two times higher in large firms compared to small firms in the average OECD country. The dispersion in adoption rates has been linked by Nicoletti et al. (2020) to obstacles in adoption contingent upon the varying strengths of capabilities and incentives across firms, industries, and countries. At the time of writing, there was a lack of systematic firm-level evidence for many developing countries.

The empirical data concerning the correlation between digital innovation investment and productivity at the level of firms or establishments are not consistently conclusive, and outcomes can significantly differ based on the chosen model specifications, the timeframe analyzed, and the industries under scrutiny. Economists' primary challenge when investigating the correlation between digital innovation and productivity pertains to the inadequacy of suitable data on digital innovation, other related inputs, and output. It is a regrettable reality that numerous industries that heavily utilize digital innovation are also the ones that exhibit the weakest measurements, according to official economic statistics. This article employs micro-level data that was previously unexplored, gathered through the Vietnamese Enterprise Survey, to examine the productivity of firms operating within the manufacturing sector. The analysis is conducted with a focus on digital innovation categories.

5. Analytical Framework

The present empirical investigation is based on the established theory of productivity. Our research focuses on the impact of digital innovation on productivity dynamics alongside conventional factors such as fixed capital, labor, wage, and years of operation. According to Aghion and Howitt (1996), innovation through research and development (R&D) is the primary driver of productivity growth. The digital economy has led to the accumulation of digital innovation on corporate balance sheets, a consequence of investments in research and development. According to Nakatani (2021), the digital economy has witnessed a significant rise in investment in intangible assets due to the increased focus of digital firms on digital innovation and outperforming their counterparts. Furthermore, we examine variations among manufacturing industries.

The analysis of the correlation between Total Factor Productivity (TFP) and digital technology aligns with the evaluation of TFP. It is worth noting that using ordinary least squares (OLS) when estimating the production function can result in significant issues. Griliches and Mairesse (1995) have indicated that firms that aim to maximize their profits tend to modify their inputs, especially capital, whenever they encounter a productivity shock, ensuring that the input levels align with the same shocks. As a result of the unobservable nature of productivity shocks, they become a constituent of the error term in the regression. Consequently, the inputs can correlate with the regression's error term, leading to biased Ordinary Least Squares (OLS) estimates of production functions. Olley and Pakes (1996) and Levinsohn and Petrin (2003) have proposed two comparable semi-parametric techniques to address this issue. Hereafter, we will refer to Olley and Pakes as OP and Levinsohn and Petrin as LP. According to Ackerberg et al.'s (2006) assertion, multicollinearity is possible in cases where there is a correlation between labor and the proxy, resulting in the inability to identify the labor coefficient. The authors Wooldridge (2009) and Petrin and Levinsohn (2012) have proposed the utilization of an instrumental variables (IVs) estimator that employs labor lags as instruments as a means of addressing this concern. Ackerberg et al. (2006) propose a technique extending the OP and LP concepts. Specifically, the method involves utilizing investment or intermediate inputs as a substitute for productivity shocks while avoiding the collinearity issues mentioned earlier. Henceforth, we shall refer to this method as AFC. In contrast to the OP and LP methodologies that compute the labor coefficient in the initial stage, where collinearity concerns emerge, the AFC approach entails computing the labor coefficient in the subsequent stage.

6. Data and Methods

6.1 Data

The present study relies on enterprise-level data from 2015 to 2019, procured by the Vietnam Annual Enterprise Census (VAES) administered by the General Statistical Office of Vietnam. The survey's fundamental unit of enumeration pertains to manufacturing firms, and the data is derived from returns furnished by the Provincial Statistical Office. The current investigation employs firm-level production parameters, including output, sales, labor, employees, capital, and materials. This dataset has been utilized in comparable studies, such as those conducted by Ngo and Tran (2020) and Ngo and Nguyen (2019).

The assignment of each enterprise code is contingent upon the industry in which the enterprise operates, with the industry that generates the largest proportion of revenues being the determining factor. The present sector classification methodology is grounded on the VSIC 2007, which aligns highly with the fourth iteration of the International Standard Industrial Classification of All Economic Activities (ISIC4 Revision).

Data about digitalized firms versus non-digitalized firms is gathered via the administration of questionnaires. The contemporary nature of production technology is associated with production equipment, which can be categorized into four types: (1) Mechanical hand tools, (2) Power-driven hand tools, (3) Human-operated machines, and (4) Computer-operated machines. Please circle the most appropriate answer.

Next, the contemporary nature of production technology/machinery/equipment concerning information and communication technology/machinery/equipment is considered. The following are examples of communication devices: (1) Telephone, (2) Mobile phone, (3) Fax machine, (4) Personal computer (without Internet connectivity), and (5) Personal computer with Internet connectivity.

Therefore, the present study defines digital economy firms as mentioned above. The three categories of computing devices are (1) automated machines controlled by computers, (2) individual computing devices lacking internet connectivity, and (3) individual computing devices with internet connectivity. The present study adopts a firm-level definition, departing from the OECD definitions as well as those proposed by Borowiecki et al. (2021), Cusolito et al. (2020), and Gal et al. (2019), among others such as Hollenstein (2004).

7. Methods

The current investigation employs an empirical model to examine the learning-by-doing hypothesis, which is based on the framework proposed by Bernard et al. (2001), Clerides et al. (1998), Kreuser and Newman (2018), and Giang et al. (2019). The model is structured as follows:

$$TFP_{it} = \alpha + \beta DT_{it} + \delta X_{it-1} + \phi TFP_{it-1} + \sum_j \delta\phi_j Time_j + \varepsilon_{it} \qquad (1)$$

where X is a vector of firm characteristics, TFP is the total factor productivity, and DT denotes digitalized firms. t and i denote year and firm, respectively, in the model. $Time_j$ is a vector of years.

The study incorporates distinct attributes of firms, such as their revenue (measured as the natural logarithm of value-added per labor), capital stock (measured as the natural logarithm of capital stocks per labor), employment size (measured as the natural logarithm of labor), human capital (measured as the natural logarithm of wage), and age (measured as the natural logarithm of years of operation). Additionally, the productivity of the preceding year is incorporated to address potential endogeneity concerns. For a comprehensive analysis of this matter, refer to Kim et al. (2009) and Giang et al. (2018). The first equation is computed individually for 14 distinct manufacturing sectors.

The estimation of Total Factor Productivity (TFP) is conducted by employing the AFC methodology, which involves utilizing value-added production as outlined by Ngo and Nguyen (2019).

The impact of firm size on total factor productivity (TFP) has been investigated in various studies (Van Biesebroeck, 2005; İmrohoroğlu and Tüzel, 2014; Malerba, 1992; Lee and Tang, 2001; Jovanovic and Nyarko, 1996). The findings suggest that larger firms positively affect TFP due to the learning-by-doing impact of their extensive experience. Conversely, research by Williamson (1967) and Tornatzky and Fleischer (1990) has determined that small enterprises exhibit greater productivity or efficacy due to their streamlined organizational framework. The determination of a firm's size is computed through the logarithmic function of the total number of employees within the organization, as posited by Giang et al. (2019), Giang et al. (2018), and Kreuser and Newman (2018).

The study incorporates an independent variable denoted as 'AGE' to assess whether younger plants exhibit superior efficiency and advanced technology compared to older plants, commonly referred to as a vintage capital effect. Alternatively, the study also examines whether learning-by-doing productivity enhances as the plant ages, as Jovanovic and Nyarko (1996) suggested.

In addition, it is theoretically recommended that the measure of capital stock employed (Harris & Drinkwater, 2000) be modified to account for vintage effects that arise due to the wear and tear of capital through usage and the fact that new capital embodies the most recent technology (resulting in the obsolescence of older vintages).

According to Isaksson's (2007), comprehensive analysis of factors influencing Total Factor Productivity (TFP), an improvement in the caliber of labor can augment the absorptive capacity, thereby facilitating the transfer of technology. The concept of labor quality, as noted by Castellani (2002) and Jung and Lee (2010), is often represented by the average wage level (WAGE).

Endogeneity remains a persistent issue when estimating total factor productivity (TFP) determinants. Including the previous year's productivity and the one-year lag of explanatory variables addresses potential endogeneity issues, as discussed in detail by Kim et al. (2009) and Giang et al. (2018).

To achieve reliable and impartial estimations of regression coefficients, we have implemented the dynamic panel generalized method of moments (GMM) estimation approach, as proposed by Blundell and Bond (1998) and Arellano and Bond (1991). The initial step of this estimator involves transforming the regression variables by applying a technique that distinguishes and eliminates the time-invariant panel-level characteristics, also known as firm-level fixed effects. The study incorporates control variables such as capital-labor ratio, number of employees, and value-added per worker, which are considered predetermined. The lagged values of these variables are utilized as exogenous instruments in implementing the GMM estimation. In this study, control variables such as a firm's age and dummies for years are considered strictly exogenous variables.

The accurate implementation of this approach is contingent upon the crucial premise of autocorrelation (Roodman, 2009), which is predominantly addressed through the utilization of lagged dependent variables as predictors. During the implementation phase, particular emphasis is placed on the assumptions regarding over-identification and homogeneity of instruments to generate valid estimations. Furthermore, this approach is well-suited for datasets with high N (number of panel firms) and low T (time-year).

8. Empirical Results

8.1 Statistical Description

Table 1 provides a statistical summary. The study's sample comprises 2,149 Vietnamese small and medium-sized enterprises (SMEs) observed repeatedly between 2015 and 2019, with at least ten employees. This resulted in a total of 10,745 observations. The balanced panel comprises comprehensive firm-specific data about total factor productivity (TFP), value-added per labor, fixed assets per labor, employment, and wage per labor.

Digital technology, encompassing computerized machinery, personal computing devices, and the worldwide web, is expounded upon in publications aimed at novice learners. Approximately 12% of small and medium-sized enterprises (SMEs) utilize computer-operated machinery in manufacturing, while 31% integrate computers into their business operations. Additionally, 29% of these SMEs use the Internet daily.

Table 1. Statistical description

Variable		Mean	Std. Dev.	Min	Max	Observations
TFP	overall	0.968	1.590	-4.584	7.337	N = 10745
	between		1.258	-3.746	4.739	n = 2149
	within		0.973	-2.348	5.621	T = 5
Computer-operated machines (Yes=1)	overall	0.120	0.325	0.000	1.000	N = 10745
	between		0.275	0.000	1.000	n = 2149
	within		0.174	-0.680	0.920	T = 5
Personal computer (without the Internet) (Yes=1)	overall	0.311	0.463	0.000	1.000	N = 10745
	between		0.366	0.000	1.000	n = 2149
	within		0.284	-0.489	1.111	T = 5
The Internet (Yes=1)	overall	0.290	0.454	0.000	1.000	N = 10745
	between		0.360	0.000	1.000	n = 2149
	within		0.276	-0.510	1.090	T = 5
Value-added per labour (million VND)	overall	246925	893508	102	26800000	N = 10745
	between		637035	561	11400000	n = 2149
	within		626653	-8167841	15700000	T = 5
Capital stocks per labor (million VND)	overall	991	1553	2	42409	N = 10745
	between		1414	8	28636	n = 2149
	within		644	-10058	16631	T = 5
Labor	overall	445	1198	11	27420	N = 10745
	between		1174	11	24073	n = 2149
	within		241	-4912	11725	T = 5
Wage per labor (million VND)	overall	108	910	0	94158	N = 10745
	between		409	6	18915	n = 2149
	within		813	-18724	75351	T = 5

9. Estimation Results

The estimation results of five distinct manufacturing sectors, namely food products (code 10), wood and products of wood/cork (code 16), paper and paper products (code 17), and printing and reproduction of recorded media (code 18), are presented in Table 2. Table 2 shows the results of pertinent tests, which demonstrate that a majority of manufacturing industries can resolve higher levels of autocorrelation (as evidenced by non-statistical AR (2) test statistics) and obtain valid instrument variables (as evidenced by non-statistical Hansen J statistics). The estimation results of five distinct manufacturing sectors, namely chemicals and chemical products (code 20), pharmaceuticals, medicinal chemicals (code 21), rubber and plastics products (code 22), other non-metallic mineral products (code 23), and fabricated metal products (code 25), are presented in Table 3. Table 3 shows the results of pertinent tests, which demonstrate the resolution of higher levels of autocorrelation (as evidenced by non-statistical AR (2) test statistics in the majority of manufacturing industries) and the attainment of valid instrument variables (as indicated by non-statistical Hansen J statistics at the common level in most manufacturing industries).

The estimation results for computer, electronic, and optical products (code 26), electrical equipment (code 27), machinery and equipment n.e.c (code 28), other transport equipment (code 30), and furniture (code 31) are presented in Table 4. The Arellano-Bond test is employed to examine the presence of second-order autocorrelation, while the Hansen J test is utilized to assess the credibility of instrumental variables. Table 4 displays findings indicating the successful resolution of elevated levels of autocorrelation and satisfactory validation of instrumental variables. The primary control variables exhibit the anticipated directionality and demonstrate the highest degree of significance, as indicated in Tables 2, 3, and 4. The findings suggest that TFP growth positively correlates with a 1% increase in value-added, which aligns with established economic theory. Additionally, the results indicate that capital and labor intensities have a detrimental effect on TFP growth. There is a correlation between lagged productivity and decreased productivity growth, indicating that firms that follow the leader can catch up with the leading firm, provided they remain in operation. The employment of digital technology has resulted in increased productivity, specifically in wood and wood/cork products. However, this effect is not universal across all manufacturing sectors, as evidenced by the lack of productivity gains in producing paper and paper products, fabricated metal products, computers, electronic and optical products, and electrical equipment.

Regarding computer machines, a noteworthy and favorable impact is observed in wood and its derivatives, including cork (classified under code 16). Conversely, a marked and unfavorable impact is noted in the domain of paper and its products (classified under code 17). Conversely, notable and unfavorable effects of the Internet on paper and paper-based commodities (category 17) are observed. The findings suggest that digital technology enhances the productivity performance of firms operating in the wood and products of the wood/cork industry (code 16). Therefore, it can be concluded that the hypothesis of learning by doing is corroborated, indicating that the utilization of digital technology impacts the productivity of the wood and wood/cork products industry. Nevertheless, it is observed that implementing digital technology does not enhance the productivity performance of firms operating in the paper and paper products industry (classified under code 17). Therefore, the hypothesis of learning by doing is not substantiated, indicating that the impact of digital technology on productivity in the paper and paper products industry is negligible. The coefficients estimated for lagged TFP in various sectors, including but not limited to food products (code 10), wood and products of wood/cork (code 16), paper and paper products (code 17), printing and reproduction of recorded media (code 18), printing and reproduction of recorded media (code 20), pharmaceuticals, medicinal chemicals (code 21), and rubber and plastics products (code 22), exhibit a significant magnitude (greater than 1), which suggests that firms in these sectors experience a sluggish adjustment of productivity over time.

Regarding the utilization of computers, notable detrimental impacts have been observed in the sectors of fabricated metal products (classified under code 25) and computer, electronic, and optical products (classified under code 26). Conversely, it has been observed that the Internet has notable and unfavorable impacts on the sectors of fabricated metal products (code 25), computer, electronic and optical products (code 26), and electrical equipment (code 27). The findings suggest that the implementation of digital technology does not enhance the productivity performance of firms operating in the fabricated metal products (code 25), computer, electronic and optical products (code 26), and electrical equipment (code 27) industries. Therefore, it can be concluded that the learning-by-doing hypothesis lacks support as there is no observable impact on productivity in fabricated metal products, computers, electronic and optical products, and electrical equipment resulting from implementing digital technology.

The regression analysis reveals that the estimated coefficients of the lagged TFP in various industries, such as other non-metallic mineral products (code 23), fabricated metal products (code 25), computer, electronic and optical products (code 26), electrical equipment (code 27), machinery and equipment (not yet classified) (code 28), and furniture (code 31), exhibit a significant magnitude (greater than 1). This suggests that firms in these industries can adjust their productivity levels quickly. However, the coefficient for other transport equipment (code 30) is an exception to this trend.

10. Conclusions and Implication

The present study offers substantial empirical support for the impact of digital technology on firm-level productivity in Vietnam. The findings indicate that the utilization of digital technology, as gauged by the frequency of computerized procedures, individual computers (excluding the Internet), and individual computers with Internet access, has a favorable influence on productivity at the organizational level. The impact of digital technology on productivity differs among firms.

The results mentioned above underscore the significance of implementing policies that facilitate sufficient digital technology to achieve productivity advantages, such as enhancing the proficiency of employees, augmenting the adoption and integration of software in tardy enterprises, and creating favorable business circumstances that can bring their productivity performance nearer to the forefront. The current study underscores valuable implications from a policy perspective that can facilitate the advancement of digital transformation and its efficacy at both the organizational and national levels. It is commendable for governmental entities to prioritize the implementation of digital strategies. As such, it is recommended that local governments incorporate this approach into their policies and facilitate the provision of platforms for businesses to adopt digital transformation. Embracing digital transformation is a complex and arduous undertaking fraught with numerous obstacles. In light of this, it is recommended that governments provide financial assistance through subsidies to mitigate the associated costs and challenges. Ensuring a firm's success and substantial economic growth in the current digital era is imperative. It is noteworthy that the implementation of digital transformation processes tends to be a gradual process. Despite the significant advantages that firms can reap in terms of enhanced operational efficiency and cost-effectiveness, there are still challenges that firms must confront during the adoption phase. It is recommended that the government create a conducive and regulatory atmosphere for businesses to facilitate the implementation of digital transformation. This would prove advantageous for the firm, as the above scenario reduces costs and diminishes the learning curve. Furthermore, it is imperative to prioritize examining the heterogeneous impact of digitalization. It is essential to adjust public policies following the ownership structure, level of sensitivity, and geographical location of firms. It is necessary to exercise stringent oversight over financial subsidies and procurement processes to ensure consistent financial backing for companies' digitalization efforts.

There exist several limitations. The GMM methodology mitigates the endogeneity issue about TFP and digital technology, leaving the possibility of endogeneity for other metrics, such as capital intensity and wage levels. Unaccounted variables, such as management proficiency, could impact productivity and capital. Productivity and wage levels may be influenced by trade or spillover effects. Moreover, digital technology assessment is somewhat constrained, as it relies on conventional technology surveys. Additionally, the study fails to account for the potential productivity implications of reallocating resources from firms with lower productivity to those with higher productivity.

11. Acknowledgement

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Table 2. The impact of digital technology on TFP

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
VARIABLES	10	10	10	13	13	13	16	16	16	17	17	17	18	18	18
L1tfp_	-10.25**	-13.94***	-9.709**	-2.620	-0.948	-3.089	-4.739***	-4.231**	-3.881***	-3.000**	-4.132**	-2.563**	-5.883	-6.595**	-6.793**
	(4.532)	(4.157)	(3.838)	(2.298)	(0.900)	(1.930)	(1.708)	(1.725)	(1.403)	(1.351)	(1.746)	(1.009)	(3.702)	(2.562)	(2.888)
pc_operated_	0.110			0.00317			0.735***			-0.483			-0.392		
	(0.479)			(0.294)			(0.219)			(0.304)			(0.702)		
L1lva_	10.57**	14.23***	10.05***	3.159	1.417	3.630*	5.169***	4.755***	4.374***	3.308**	4.371***	2.999***	6.080*	6.682***	6.860**
	(4.516)	(4.137)	(3.823)	(2.314)	(0.929)	(1.957)	(1.666)	(1.689)	(1.388)	(1.286)	(1.652)	(0.973)	(3.519)	(2.536)	(2.798)
L1lkl_	-6.137**	-8.423***	-5.840**	-1.597	-0.672	-1.874*	-3.203***	-2.895***	-2.665***	-2.146**	-2.834***	-1.905***	-4.144*	-4.534***	-4.717**
	(2.733)	(2.514)	(2.323)	(1.226)	(0.494)	(1.032)	(1.075)	(1.078)	(0.903)	(0.859)	(1.095)	(0.628)	(2.431)	(1.701)	(1.899)
L1ll_	-12.24**	-16.48***	-11.63***	-3.627	-1.647	-4.171*	-5.499***	-5.040***	-4.617***	-4.715***	-6.267***	-4.291***	-8.522*	-9.322***	-9.685**
	(5.230)	(4.792)	(4.433)	(2.624)	(1.051)	(2.220)	(1.792)	(1.814)	(1.493)	(1.816)	(2.346)	(1.375)	(4.936)	(3.531)	(3.899)
L1lwage_	-0.249	-0.261	-0.243	-0.112	-0.0738	-0.139	-0.353**	-0.380**	-0.340*	-0.190	-0.236	-0.360**	-0.353**	-0.348*	-0.280*
	(0.172)	(0.168)	(0.169)	(0.154)	(0.151)	(0.134)	(0.176)	(0.190)	(0.186)	(0.175)	(0.147)	(0.151)	(0.157)	(0.200)	(0.164)
lage_	-2.103	-3.069*	-1.845	0.692	0.982	0.903	-1.116**	-1.449***	-1.340***	-1.288	-0.967	-0.286	0.600	0.751	1.472
	(1.685)	(1.709)	(1.588)	(0.983)	(0.853)	(1.059)	(0.496)	(0.478)	(0.465)	(2.742)	(2.307)	(3.207)	(1.923)	(2.379)	(2.018)
lage_2	0.301	0.485	0.249	-0.126	-0.193	-0.167	0.274**	0.348***	0.320**	0.222	0.162	0.0507	-0.0985	-0.128	-0.218
	(0.310)	(0.321)	(0.295)	(0.189)	(0.159)	(0.202)	(0.138)	(0.129)	(0.126)	(0.445)	(0.374)	(0.533)	(0.272)	(0.348)	(0.287)
pc_		0.349			0.112			-0.264			0.0698			-0.194	
		(0.374)			(0.176)			(0.318)			(0.172)			(0.352)	
internet_			-0.309			0.0290			0.321			-0.320			-0.235
			(0.327)			(0.205)			(0.390)			(0.222)			(0.301)
Observations	1,131	1,131	1,131	449	449	449	392	392	392	456	456	456	181	181	181
Number of IDs	285	285	285	116	116	116	104	104	104	119	119	119	48	48	48
Hansen J statistic	43.28	41.65	41.78	27.44	40.29	31.06	30.44	35.21	33.66	29.30	28.37	31.04	17.01	16.57	16.19
the p-value of Hansen's statistic	4.44e-06	8.64e-06	8.20e-06	0.00221	1.51e-05	0.000573	0.000725	0.000115	0.000211	0.00111	0.00157	0.000577	0.0486	0.0843	0.0942
Wald chi-squared statistic	663.8	652.9	631.5	1872	2784	1734	994	1021	995.8	787.7	815	1119	384.1	126.4	291.3
the p-value of Wald statistic	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AR(2) test statistic	-1.310	-0.955	-1.345	-0.203	0.355	-0.299	0.463	0.283	-0.0751	-0.697	-0.970	-0.288	-0.975	-1.717	-1.521
p-value of AR(2) statistic	0.190	0.340	0.179	0.839	0.723	0.765	0.643	0.777	0.940	0.486	0.332	0.773	0.330	0.0860	0.128
Number of instruments	22	22	22	22	22	22	22	22	22	22	22	22	21	22	22

Note: The under-identification test is an LM test: The null hypothesis is whether the equation is identified, i.e., the excluded instruments are relevant, meaning correlated with the endogenous regressors. Test of over-identification restrictions (The Sargan-Hansen test): The joint null hypothesis is that the instruments are valid, i.e., uncorrelated with the error terms and that the excluded instruments are correctly excluded from the estimated equation. Test of weak identification: The null hypothesis of the Kleibergen-Paap ranking LM statistics is that the equation is under-identified. Test of exogeneity of instruments (C statistics): The null hypothesis that suspects instruments are valid. Standard errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3. The impact of digital technology on TFP

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
VARIABLES	20	20	20	21	21	21	22	22	22	23	23	23	25	25	25
L1tfp_	-6.682***	-6.273***	-6.191***	-0.0520	-0.674	-0.324	-6.629**	-6.419**	-8.492*	-3.780**	-4.092**	-4.403**	-3.933***	-2.857***	-4.027***
	(2.337)	(2.282)	(2.194)	(0.397)	(0.447)	(0.379)	(3.214)	(3.038)	(4.512)	(1.684)	(1.964)	(2.211)	(1.413)	(0.782)	(1.225)
pc_operated_	0.269			0.321			-0.318*			0.438**			-0.257		
	(0.235)			(0.553)			(0.180)			(0.213)			(0.271)		
L1lva_	6.826***	6.478***	6.414***	0.163	0.680*	0.387	6.910**	6.744**	8.726**	4.134**	4.501**	4.799**	4.140***	3.103***	4.241***
	(2.295)	(2.243)	(2.164)	(0.322)	(0.369)	(0.254)	(3.121)	(2.987)	(4.399)	(1.663)	(1.951)	(2.195)	(1.337)	(0.755)	(1.173)
L1lkl_	-4.538***	-4.273***	-4.380***	-0.266	-0.817*	-0.529**	-4.565**	-4.437**	-5.770**	-2.699**	-2.877**	-3.079**	-3.463***	-2.624***	-3.547***
	(1.613)	(1.568)	(1.539)	(0.267)	(0.435)	(0.261)	(2.074)	(1.958)	(2.913)	(1.102)	(1.281)	(1.444)	(1.132)	(0.633)	(0.980)
L1ll_	-7.579***	-7.145***	-7.150***	-0.240	-0.897**	-0.562*	-7.414**	-7.245**	-9.362**	-4.731**	-5.091**	-5.439**	-4.642***	-3.481***	-4.762***
	(2.566)	(2.497)	(2.428)	(0.350)	(0.442)	(0.290)	(3.363)	(3.217)	(4.734)	(1.896)	(2.218)	(2.492)	(1.501)	(0.839)	(1.314)
L1lwage_	-0.0937	-0.241	0.0495	0.128	0.180	0.213	0.150	0.0772	0.0599	-0.143	-0.164	-0.168	-0.310**	-0.241*	-0.341**
	(0.318)	(0.268)	(0.288)	(0.223)	(0.254)	(0.217)	(0.205)	(0.203)	(0.190)	(0.133)	(0.127)	(0.122)	(0.142)	(0.130)	(0.140)
lage_	8.588***	7.671**	8.556***	-0.672	0.166	2.394	-0.317	-0.286	-0.339	0.256	0.359	0.300	-0.0981	-0.158	-0.104
	(2.886)	(3.091)	(2.922)	(4.188)	(3.833)	(4.047)	(0.503)	(0.483)	(0.550)	(0.757)	(0.719)	(0.752)	(0.265)	(0.281)	(0.228)
lage_2	-1.390***	-1.236**	-1.362***	0.123	0.0145	-0.352	0.0564	0.0505	0.0668	-0.0249	-0.0384	-0.0306	0.0391	0.0485	0.0458
	(0.511)	(0.550)	(0.506)	(0.668)	(0.587)	(0.637)	(0.0925)	(0.0896)	(0.106)	(0.123)	(0.113)	(0.119)	(0.0598)	(0.0614)	(0.0489)
pc_		-0.377			0.221			-0.0476			0.203			-0.300	
		(0.351)			(0.358)			(0.186)			(0.181)			(0.196)	
internet_			0.138			-0.365*			-0.107			-0.0696			-0.347**
			(0.328)			(0.199)			(0.291)			(0.150)			(0.164)
Observations	519	519	519	130	130	130	820	820	820	709	709	709	829	829	829
Number of IDs	135	135	135	33	33	33	215	215	215	179	179	179	221	221	221
Hansen J statistic	11.97	13.76	19.20	12.31	18.95	15.44	46.94	49.98	47.09	59.30	53.21	49.46	53.90	49.68	49.23
the p-value of Hansen's statistic	0.287	0.184	0.0378	0.196	0.0410	0.117	9.69e-07	2.69e-07	9.10e-07	4.92e-09	6.82e-08	3.36e-07	5.07e-08	3.06e-07	3.69e-07
Wald chi-squared statistic	840.5	784.6	883.5	1170	816.8	1127	2111	2114	2489	1116	1222	1329	445.1	393.7	457.1
the p-value of Wald statistic	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AR(2) test statistic	-0.893	-0.654	-0.521	-0.286	0.731	-0.406	-0.365	-0.302	-0.560	0.611	0.537	0.701	-1.418	-1.484	-1.255
p-value of AR(2) statistic	0.372	0.513	0.602	0.775	0.465	0.685	0.715	0.763	0.576	0.541	0.591	0.483	0.156	0.138	0.210
Number of instruments	22	22	22	21	22	22	22	22	22	22	22	22	22	22	22

Note: The under-identification test is an LM test: The null hypothesis is whether the equation is identified, i.e., the excluded instruments are relevant, meaning correlated with the endogenous regressors. Test of over-identification restrictions (The Sargan-Hansen test): The joint null hypothesis is that the instruments are valid, i.e., uncorrelated with the error terms and that the excluded instruments are correctly excluded from the estimated equation. Test of weak identification: The null hypothesis of the Kleibergen-Paap ranking LM statistics is that the equation is under-identified. Test of exogeneity of instruments (C statistics): The null hypothesis that suspects instruments are valid. Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 4. The impact of digital technology on TFP

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
VARIABLES	26	26	26	27	27	27	28	28	28	30	30	30	31	31	31
L1tfp_	-2.669	-2.726***	-2.356*	-7.054**	-8.376**	-7.499*	-0.694**	-0.784*	-0.758**	-0.280**	-0.307***	-0.309***	-2.522***	-2.719***	-2.262***
	(1.883)	(1.045)	(1.353)	(3.005)	(3.890)	(4.070)	(0.308)	(0.422)	(0.344)	(0.116)	(0.110)	(0.0930)	(0.617)	(0.641)	(0.705)
pc_operated_	0.0955			-0.00962			-0.450*			0.0144			0.0775		
	(0.559)			(0.385)			(0.271)			(0.210)			(0.176)		
L1lva_	2.932	2.985***	2.694*	7.191**	8.438**	7.704*	1.103***	1.168**	1.001**	0.302*	0.317	0.306*	2.750***	2.969***	2.533***
	(1.867)	(1.034)	(1.441)	(2.882)	(3.731)	(3.947)	(0.332)	(0.525)	(0.453)	(0.173)	(0.197)	(0.177)	(0.600)	(0.605)	(0.668)
L1lkl_	-2.241	-2.233***	-1.982*	-5.009***	-5.840**	-5.313**	-0.510***	-0.610***	-0.547***	-0.391**	-0.376**	-0.423***	-1.446***	-1.532***	-1.330***
	(1.451)	(0.774)	(1.076)	(1.937)	(2.515)	(2.655)	(0.165)	(0.224)	(0.193)	(0.168)	(0.182)	(0.148)	(0.301)	(0.310)	(0.349)
L1ll_	-3.206	-3.199***	-2.882*	-8.492**	-9.952**	-9.069*	-1.198***	-1.266**	-1.088**	-0.542**	-0.526**	-0.495**	-2.835***	-3.067***	-2.602***
	(2.033)	(1.133)	(1.542)	(3.398)	(4.408)	(4.651)	(0.374)	(0.593)	(0.505)	(0.230)	(0.262)	(0.221)	(0.631)	(0.634)	(0.706)
L1lwage_	-0.186	-0.294	-0.306	-0.114	-0.108	-0.222	0.0256	0.0400	0.151	-0.136	-0.152	-0.163	0.00552	-0.00469	0.0331
	(0.205)	(0.218)	(0.197)	(0.159)	(0.162)	(0.167)	(0.262)	(0.356)	(0.338)	(0.245)	(0.224)	(0.228)	(0.132)	(0.120)	(0.119)
lage_	-21.43*	-14.80	-20.57***	4.467**	4.542**	2.642	1.925	-0.241	1.230	1.232	-0.337	2.232	0.0920	0.110	0.141
	(12.51)	(10.85)	(7.759)	(2.145)	(1.998)	(1.660)	(1.915)	(1.861)	(2.069)	(7.508)	(9.892)	(6.397)	(0.300)	(0.277)	(0.315)
lage_2	3.832*	2.659	3.690***	-0.756**	-0.755**	-0.421	-0.359	0.0175	-0.226	-0.196	0.0511	-0.420	-0.0128	-0.0120	-0.0248
	(2.245)	(1.931)	(1.379)	(0.352)	(0.323)	(0.282)	(0.329)	(0.310)	(0.344)	(1.400)	(1.851)	(1.178)	(0.0729)	(0.0642)	(0.0724)
pc_		-0.961**			0.0607			-0.0450			0.0883			0.0536	
		(0.407)			(0.257)			(0.221)			(0.335)			(0.0856)	
internet_			0.0741			-0.812*			0.281			-0.200			0.0299
			(0.357)			(0.457)			(0.320)			(0.242)			(0.178)
Observations	142	142	142	293	293	293	230	230	230	151	151	151	573	573	573
Number of IDs	37	37	37	76	76	76	63	63	63	40	40	40	147	147	147
Hansen J statistic	20.41	15.15	22.21	17.42	18.10	22.59	24.38	27.19	24.01	13.76	16.31	14.28	18.30	15.04	16.10
the p-value of Hansen's statistic	0.0155	0.127	0.0140	0.0656	0.0534	0.0124	0.00665	0.00243	0.00758	0.131	0.0911	0.161	0.0501	0.131	0.0968
Wald chi-squared statistic	407.8	371.2	417.7	358.6	384.3	349.4	4219	3956	3609	1290	1058	1735	11887	12959	13638
the p-value of Wald statistic	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AR(2) test statistic	0.127	0.699	0.436	1.041	0.884	0.543	-0.632	-0.180	-0.433	0.264	-0.0587	-0.442	0.692	0.909	0.588
p-value of AR(2) statistic	0.899	0.485	0.663	0.298	0.377	0.587	0.527	0.857	0.665	0.792	0.953	0.658	0.489	0.363	0.557
Number of instruments	21	22	22	22	22	22	22	22	22	21	22	22	22	22	22

Note: The under-identification test is an LM test: The null hypothesis is whether the equation is identified, i.e., the excluded instruments are relevant, meaning correlated with the endogenous regressors. Test of over-identification restrictions (The Sargan-Hansen test): The joint null hypothesis is that the instruments are valid, i.e., uncorrelated with the error terms and that the excluded instruments are correctly excluded from the estimated equation. Test of weak identification: The null hypothesis of the Kleibergen-Paap ranking LM statistics is that the equation is under-identified. Test of exogeneity of instruments (C statistics): The null hypothesis that suspects instruments are valid. Standard errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

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