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Theorizing the relationship between the digital economy and firm productivity: The idiosyncrasies of firm-specific contexts

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A R T I C L E I N F O

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A B S T R A C T

With the rise of emerging economies such as China, the research environment for the digital economy (DE) has changed significantly. However, our understanding of the productivity impact of DE development in Chinese firms remains in its infancy. The idiosyncrasies of the firm-specific contexts are closely related to further research on the this topic. As a baseline, we hypothesize a U-shaped DE-firm productivity (FP) relationship. We analyze the idiosyncratic influences of firm size and locality on the DE–FP relationship. The findings, which are based on a sample of Chinese firms from 2016 to 2019, show that (a) the U-shaped DE–FP relationship applies to Chinese firms; (b) this relationship is moderate for large firms, substantially steeper for medium firms, and inverted for small firms; (c) the U-shaped DE–FP relationship for eastern region firms is moderate, while the U-shaped relationship for central region firms is steep, but the transition is incomplete, and western region firms have experienced increasing productivity since the early stage of DE development. This study offers an alternative approach to understanding Chinese firms' strategic choices in DE development and provides a more nuanced explanation for the productivity paradox by emphasizing the significance of the firm-specific context. In this way, the study captures the sophisticated and constantly evolving relationships between DE and FP for heterogeneous Chinese firms.

1. Introduction

According to the 2016 G20 Digital Economy Development and Cooperation Initiative, the digital economy (DE) is a collection of economic activities in which digitized knowledge and information serve as essential factors of production, the modern information network functions as a key carrier, and the effective use of information and communication technology (ICT) is a significant driving force for efficiency improvement and ecological sustainability. Notably, DE has become increasingly important in increasing global productivity.

Many empirical studies have examined the relationship between the efficient use of ICT and productivity. Unfortunately, these attempts have yielded inconsistent, if not conflicting, results. Solow (1987) coined the term "productivity paradox" to describe the fact that the rapid development of ICT-related industries has not brought about a significant increase in productivity. Several subsequent studies have evaluated the validity of the productivity paradox in developed countries, such as the United States, the United Kingdom, and Japan. Dewan and Kraemer (2000) and Stanley et al. (2018) concluded that the paradox had vanished in developed countries, while Lin and Shao (2006) observed its persistence.

Most studies on the productivity paradox have taken place in developed countries. However, the research environment has undergone remarkable changes with the rise of emerging economies, such as China. DE development has emerged as a prominent strategy and a key driver of high-quality growth in China (Pan et al., 2022), with significant

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productivity implications (Cai and Zhang, 2015; Li and Wu, 2020; Sun et al., 2012) and opportunities to understand the productivity consequences for Chinese firms, both theoretically and empirically. The growing relevance of DE in today's competitive environment has prompted research on the digitization strategies of Chinese firms (Heshmati and Kumbhakar, 2011; Lee et al., 2011; Liu et al., 2014; Sun et al., 2017). As more Chinese firms undergo digital transformation, understanding the effects of digitization initiatives is vital. The various strategies employed by Chinese firms in the DE era may impact productivity, but the extent of this impact is unclear. This constitutes a significant omission in the existing research.

More importantly, scholars have recently acknowledged the need to identify the idiosyncrasies of firm-specific contexts in considering firms' digitization strategies (e.g., Lin and Shao, 2006). Consistent with this viewpoint, Lin and Shao (2006) reported that firm size influences the payoffs of digitization. It is, however, empirically uncertain whether DE is more beneficial or detrimental to large, medium, or small firms (Sun et al., 2017). In addition, a firm's locality influences its digitization strategy as well as its potential to improve efficiency (Pan et al., 2022). We do not yet know whether the productivity paradox persists or vanishes in Chinese regions at various stages of DE development (Chen and Xie, 2015).

Previous studies have assumed firm-specific contexts to be "mere background" information in addressing Chinese firms' digitization choices. They have thus largely ignored the importance of firm size and firm locality in shaping those choices. This is a significant lacuna in the literature because while all firms place a premium on DE growth, firms vary greatly by firm size and locality. Without a thorough knowledge of the effects of size and locality on firms' strategic choices and productivity, it becomes challenging to comprehensively analyze the productivity outcomes of Chinese firms' digitization strategies.

Our analysis addresses these gaps by merging the literature on DE, firms' strategic choices, and firm-specific contexts. More explicitly, we extend previous research to Chinese firms and incorporate the idiosyncrasies of firm-specific contexts into the DE–FP model. As previously indicated, inconsistent findings in the ICT–productivity relationship prompted us to conduct this study. We also respond to the increasingly acknowledged need to rethink conventional wisdom regarding the ICT–productivity relationship in the context of Chinese firms. We found that the DE–FP relationship is curvilinear, meaning that the productivity paradox persists at the early stage of DE development but gradually fades as DE progresses. While prior research on the productivity paradox has implied a linear relationship (e.g., Dewan and Kraemer, 2000; Lin and Shao, 2006), we propose a non-linear relationship (e.g., Chen and Xie, 2015).

Our study was also motivated by the need to examine the role of firm-specific idiosyncrasies in firms' strategic choices and productivity in the development of the DE in China. Prior studies have largely neglected these endeavors. We include firm-size and firm-locality variables to investigate the impact of firm-specific contexts. Our study demonstrates that a moderate curvilinear relationship is particularly evident in firms in China's eastern region and in large firms, whereas the curvilinear relationships are steep in central region firms and in medium firms. Meanwhile, the U shape is inverted for small firms, and western region firms have experienced increasing productivity since the early stage of DE development.

Using an unbalanced panel data set of 10,739 observations on Chinese listed firms for the 2016–2019 period, we tested the influence of firm size and firm locality on the DE–FP relationship. We then applied the China "Internet Plus" Digital Index to measure the most recent developments in the DE–FP relationship. In addition, we used the Hausman test to determine whether a productivity paradox exists in China based on the panel data fixed effect model and illustrate DE's impact on FP in a systematic manner. We also conducted sub-sample analyses by firm size and locality to empirically examine the DE–FP relationship across firms of varying sizes or from various regions. Our empirical context is China, which is undoubtedly the most active economy in the world in terms of DE development. In fact, China's DE development has overtaken that of the United Kingdom and Japan, and it now ranks second in the world. The China Academy of Information and Communications Technology (2021) published a white paper on the development of China's DE, estimating that the volume of DE reached 39.2 trillion yuan in 2020 and accounted for 38.6 % of the country's GDP; this represented an increase of 3.3 trillion yuan from the previous year. We predict, moreover, that China's position in the global DE will continue to improve because of its significant latecomer advantage. Therefore, it is necessary to develop a deeper understanding of the role that Chinese firms play in the competitive DE environment.

This research is structured into the following sections. Section 2 proposes the theoretical framework and develops the hypotheses; Section 3 describes the methodology, including the sample information and variables; Section 4 analyses the empirical results; and Section 5 discusses the findings and provides conclusions from the research.

2. Theoretical framework and hypotheses development

2.1. Firms' digitization strategies: digitized versus non-digitized

At a basic level, firms can choose between two types of digitization strategies: digitized and non-digitized. These two types of strategies vary in five aspects. According to the framework in Table 1, the first characteristic of a digitized strategy is that firms using it believe their value creation derives from heterogeneous production and services; hence, they focus on offering high-quality heterogeneous products and services (Porter and Heppelmann, 2016). The second critical feature of a digitized strategy is that firms rely on their extremely proactive and innovative employees to engage in creative work (Frynas et al., 2018). Third, a digitized strategy necessitates a high degree of diversification for firms to run efficiently. In other words, firms must implement diversification to realize the complex economy of scope. The fourth characteristic of a digitized strategy is that it is often organized into a small-world network with a flat structure (Cui et al., 2015; Porter and Heppelmann, 2016). The last characteristic of a digitized strategy is that a firm's resource allocation is defined by network-based mechanisms in which the supply and demand sides are linked inside a network; these might include one-to-one targeted marketing, contextual pricing, and partnership (Cheng et al., 2018; Xie et al., 2016).

Firms with a non-digitized strategy, on the other hand, focus on producing a large volume of homogeneous goods and services (Acemoglu and Restrepo, 2018). In general, firms that pursue a non-digitized strategy believe that their homogeneous goods and services create value. In a non-digitized firm, the organization is structured bureaucratically in a pyramid form (Ward et al., 2005). Employees work in a standardized manner, with managers determining their work's style and substance. Managers expect employees to be highly specialized in order to work better with machines and gain economies of scale from homogeneous

Table 1
Digitization strategies of firms: Differences between non-digitized and digitized strategies.

	Non-digitized strategy	Digitized strategy
1. Orientation	Quantity oriented: production and services homogeneity	Quality oriented: production and services heterogeneity
2. Labor force	Standard, reactive	Creative, active
3. Technological paradigm	High specialization for the economy of scale	High diversification for the economy of scope
4. Organizational management	Pyramid-shaped, bureaucracy	Small-world network, flat structure
5. Resource allocation	Market mechanism based on price competition	Network mechanism based on quality competition

Source: Own elaboration.

production. In this way, non-digitized firms are able to participate in the market mechanism of resource allocation based on price competition for their homogeneous goods and services.

2.2. The choices of firms' digitization strategies in the context of DE development

Using the framework described above for firms' digitization strategy, we next investigate how firms choose between alternative digitization strategies. To address this question, we analyze the cost structures of the two types of strategy at various stages of DE development as well as the associated productivity advantages.

DE development includes well-developed digital technology, digital infrastructure, digital finance, and digital government. Assuming that DE development is exogenous, the fixed cost for firms to use it will be minimal once it is established. In other words, advanced DE development allows firms to adopt a digitized strategy at a minimal fixed cost and a minimal and declining marginal cost. Specifically, the integration of digital technology enables the low-cost implementation of a flat and flexible organizational structure with small-world networks and motivated employees (Bloom et al., 2016). In Haier's "ren dan he yi," for example, the terms "ren" and "dan" refer to employees and user orders, respectively. Simply put, "ren dan he yi" indicates that a firm breaks its objectives down into user orders and assigns those orders to the appropriate employees who are accountable for them. The management department evaluates employees' performance by assessing the fulfillment of each order. "Ren dan he yi" is a creative model that allows firms to become platforms for integrating global resources. When they are trusted and empowered, employees can fully unleash their potential, achieve self-growth, and create value for users. Through zero-distance employee–user interactions, moreover, firms can better understand customers' personalized demands and provide them with heterogeneous goods (Frynas et al., 2018). Notably, embedding DE facilitates the formation of small-world networks both inside and outside of firms. For instance, instant office communication software, such as WeChat, DingTalk, and Lark, enable rapid communication between various departments within firms and between the firm and the external environment (Bauer et al., 2015). This significantly improves communication efficiency and lowers information transmission costs.

More importantly, a digitized strategy encourages firms to focus on diversification and achieve economies of scope at a low cost through cross-boundary operations. DE development, moreover, makes this easier. First, the development of new-generation ICT provides firms with digital R&D tools that allow them to attain product diversification at extremely low marginal costs. For example, digital simulation systems and virtual reality technology (Graetz and Michaels, 2018) allow firms to simulate physical entities, which enables the R&D of diversified varieties in complex application scenarios (Zhang et al., 2018). The development of new-generation ICT also minimizes resource losses associated with repetitive mold development, thus lowering R&D costs (Vaccaro et al., 2011).

Second, the development of the DE helps firms to achieve a more precise and efficient manufacturing process while reducing production costs. Firms can integrate dispersed production data into a unified production management system using digital technologies, such as big data, artificial intelligence, and the Internet of Things (Frynas et al., 2018). Decentralized and intermittent states of R&D, design, manufacturing, and quality control can be transformed into continuous and integrated states via DE advancement (Bloom et al., 2016). This has the potential to significantly increase the efficiency and precision of production. For example, the Midea Group engages in data exchanges with suppliers by utilizing its supplier collaboration cloud. Suppliers gain real-time access to Midea's current inventory and manufacturing schedule. Meanwhile, Midea has access to suppliers' material inventory and logistical data. The production arrangement can thus be tailored to each manufacturing line and hour, resulting in accelerated delivery and increased productivity.

Third, the flow of data resources among different industries has become a typical example in the new DE business format, blurring the boundaries between industries (Cui et al., 2015). Cross-border operations allow firms to distribute resources more efficiently and achieve economies of scope. Manufacturing firms might leverage big data to provide customers with tailored value-added services and shift from homogeneous to heterogeneous manufacturing depending on customer experiences. Service firms might also evolve from single-service suppliers to multi-service providers and platforms. As a traditional real estate middleman, Lianjia has evolved into one of the industry's first models of a cross-border operator using digital technology. Lianjia launched an online real estate service platform, "Lianjia Online" (later called lianjia.com), in 2010. In 2013, barely four years after the Internet platform was founded, lianjia.com accounted for 24 % of Lianjia's total income. This example demonstrates that firms may overcome industry barriers in the context of DE, enabling the efficient and effective allocation of resources across industries and the achievement of economies of scope (Dyer et al., 2018).

Furthermore, due to the development of DE, firms can achieve high productivity through network-based resource allocation mechanisms. For example, during a product's R&D stage, firms can collect user data, such as transaction information and evaluation feedback, to analyze consumer needs and establish a precise connection between product innovation and consumer demand. This information, in turn, provides a critical reference for firms to assess market demand and potential business risks (He et al., 2019). In contrast, R&D staff cannot precisely comprehend the actual needs of customers in the conventional closed R&D paradigm; therefore, innovation failure often results (Cheng et al., 2018). DE has successfully overcome this challenge and significantly reduced the trial-and-error costs and innovation risks associated with R&D (Johnson et al., 2017). Meanwhile, a new-generation ICT-based digital collaborative innovation platform has created an open innovation environment (Mikalef and Pateli, 2017). This platform allows prospective players to participate in a firm's R&D and innovation processes (Varian, 2010). The use of a digital collaborative innovation platform can considerably reduce the search costs for R&D resources and efficiently integrate dispersed R&D resources (Cui et al., 2015).

The Xiaomi ecosystem is an example of a supplier-side network-based mechanism of resource allocation. The Xiaomi ecosystem is built on its IoT development platform, which is an open platform with extensive support. All Xiaomi ecosystem firms as well as third-party developers interested in connecting their hardware products to the Xiaomi platform are welcome to access and use these services. Such firms can maximize their profits by using the open platform and its derived low (or even zero) entrance costs. From the demand-side network-based mechanism of resource allocation, a digital platform integrating various firms' business information has arisen, bridging the information divide between lenders and borrowers. Gathering necessary information and effectively determining the true status of firms from traditional banking institutions is challenging (Brown et al., 2009). Such institutions are often hesitant to lend when extensive information asymmetry exists. One of the implications is that firms face severe financing constraints, thus limiting investment in R&D and innovation (Howell, 2015).

The use of digital technology expands opportunities for disseminating information and increases the efficiency of obtaining information. Meanwhile, the growth of digital finance has intensified competition in the financial sector and expanded external financing channels. The emergence of this novel business format has significantly improved the matching efficiency of credit resources and successfully resolved the issue of financing constraints. For example, Sesame Credit is a private credit scoring and loyalty program system developed by Alibaba Group. Through its own e-commerce platforms, such as Taobao, Alipay, and Tmall, Alibaba Group has accumulated rich data on small and micro enterprises in the fields of trade, distribution, logistics, and customer evaluation. These data have been used to determine the creditworthiness of small and micro firms. Sesame Credit delivers dependable credit investigation services on this premise. Credit audits, which formerly required a significant amount of time, effort, and offline operations, have been steadily phased out, significantly increasing firms' financing efficiency. Additionally, governments can utilize the digital information platform to assess firms' innovation potential and facilitate the efficient allocation of innovation subsidies, tax incentives, and other policy resources (Chen and Xie, 2015).

Nevertheless, firms may, at some point, encounter a "digital vacuum" (Stieglitz et al., 2016). During the DE transition, the application of the traditional non-digitized strategy declines, while the new digitized strategy is not yet effective, resulting in a digital vacuum. We argue that this digital vacuum often occurs when DE development is at a moderate stage (neither excessively low nor extremely high; Brynjolfsson and Hitt, 2000). At this point, firms create certain internal digital infrastructure and bear the expense of doing so endogenously. Compared to the early stage of DE development, firms have a reduced fixed cost at the moderate stage. However, firms sometimes bear significant marginal costs associated with compatibility difficulties (Dyer et al., 2018; Ward et al., 2005). For example, employees must adjust to a new work pattern that shifts them from reactive to proactive work, although many of them are unfamiliar with these changes (Ward et al., 2005).

It is increasingly critical for employees to gain new skills and ways of thinking (Stieglitz et al., 2016; Xie et al., 2016) to adapt to the use of a digitized strategy. Hence, firms must, therefore, increase investment in professional training for employees and recruit new employees (Matt et al., 2015; Watson, 2017). Meanwhile, the emergence of new technologies poses significant problems and threats to network and data security (Kim et al., 2015). As a result, it imposes additional expectations on employees' data availability cognition (Wagner et al., 2012) as well as their knowledge regarding relevant laws and ethics (Agarwal et al., 2010). Consequently, labor costs increase (Acemoglu and Restrepo, 2018; Borland and Coelli, 2017; Frey and Osborne, 2017).

Additionally, firms may fail to develop the necessary organizational coordination to capitalize on the benefits associated with the DE (Arvanitis and Loukis, 2009). Typically, when firms implement digital technology as a new power, they must systematically adjust their manufacturing, commercial, and organizational processes to achieve compatibility (Porter and Heppelmann, 2016). Internal communication via a digital platform may impair the flexibility and openness of the information processing and transmission processes, resulting in information distortion and further impairing decision-making efficiency (Pesch and Endres, 2019). In sum, personnel transformation and compatibility issues that emerge during the moderate stage of DE development make it difficult to realize the payoffs of the DE while also increasing fixed and marginal costs when firms opt for a digitized strategy.

In comparison, when DE development is in its infancy and firms opt for a digitized strategy, they must construct these digital infrastructures entirely on their own. The fixed cost thus becomes endogenous, making digitization expensive for firms and ultimately affecting productivity. In such cases, it is more productive for firms to maintain a non-digitized strategy (i.e. homogeneous production and services) rather than a digitized one. Based on the above, Fig. 1 presents a quadrant diagram illustrating the cost structures of digitized and non-digitized strategies at various stages of DE development. The horizontal axis depicts the stages of DE development, while the vertical axis shows firms' digitization strategies. In the first quadrant, at an advanced stage of DE development, firms would opt for a digitized strategy with exceptionally low fixed and marginal costs. Firms in the second quadrant, meanwhile, would adopt a digitized strategy at the early stage of DE development. The fixed and marginal costs would be high for firms in this scenario because the cost of developing digital technology and infrastructure must be internalized. In the third quadrant, firms would select a non-digitized strategy at the early stage of DE development. Here, both the

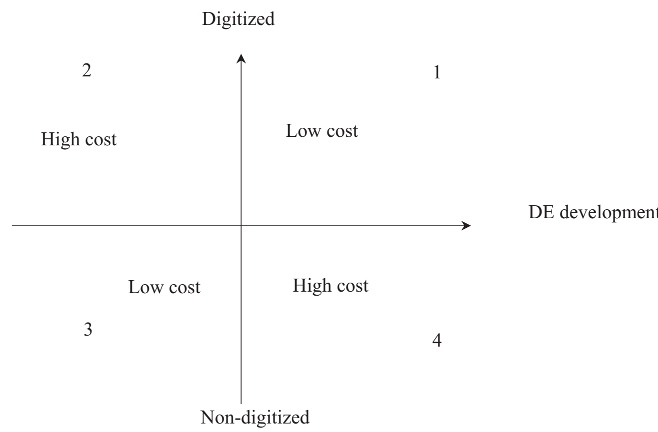


Fig. 1. Cost structure of the digitization strategy at various stages of DE development.
Source: Own elaboration.

fixed and marginal costs would be minimal. The fourth quadrant is the most unique, with firms opting for a non-digitized strategy at an advanced stage of DE development. In this scenario, non-digitized firms would face strong competition from digitized firms, forcing them to devote considerable human and physical resources to improving their homogeneous goods and services and thus increasing costs.

Considering the various cost structures of digitization strategies at different stages of DE development, the productivity (cost) advantage of a non-digitized strategy makes it the most logical choice for firms at the early stage of DE development. However, at the moderate stage of DE development, firms might opt to endure the painful transition from a non-digitized to a digitized strategy to better compete in the future when DE development progresses to an advanced stage. Because firms are likely to encounter personnel and organizational compatibility difficulties, productivity plummets at this stage. When DE reaches a mature level, the digitized strategy becomes the most sensible choice due to its remarkable productivity benefits.

Fig. 2 illustrates the productivity advantages of digitized and non-digitized strategies. The thick curve depicts the theoretical relationship between DE and FP as DE develops. In sum, the relationship between the DE and FP will be curved (U-shaped).

Thus, we proposed the following hypothesis:

Hypothesis 1. A U-shaped relationship exists between the development of DE and FP.

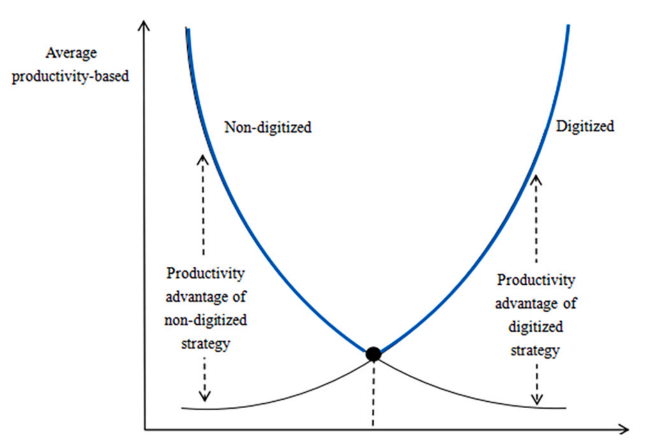


Fig. 2. Productivity advantage of digitized and non-digitized strategies.
Source: Own elaboration.

2.3. The idiosyncrasies of firm-specific contexts

As previously stated, we argue that firms will experience a digital vacuum when transitioning from a non-digitized to a digitized strategy. However, the duration of this digital vacuum moment will vary across firms in different contexts, depending on the difficulty they encounter in resolving compatibility issues during the transition to and development of the DE (Howell, 2015). Thus, the firm-specific context is critical. In this paper, we concentrate on two critical firm-specific contexts: firm locality and firm size.

2.3.1. Firm locality

China is an expansive country characterized by distinct DE development stages in its eastern, central, and western regions. The eastern region is the most developed in terms of the DE, and eastern firms are more advanced in their digital transformation than are those in the central and western regions (Pan et al., 2022). As the first mover in the digital transformation, however, eastern firms have less expertise with transition and compatibility concerns. Due to their inexperience and the need for more complicated digital infrastructure to support their operations, firms in the eastern region may experience a lengthier productivity decline. The link between the DE and FP, in turn, may assume a moderate U-shaped structure in this scenario.

Firms in the central region, while at a less developed DE stage, may benefit from a latecomer advantage when transitioning to a digitized strategy. By developing their digital strategy later than firms in the eastern region, they may experience a shorter digital vacuum (Bonfadelli, 2002). However, firms in the central region require sophisticated digital technology and infrastructure to enable their digital transformation. Therefore, they may choose to maintain their existing non-digitized strategy to preserve comparatively higher but rapidly dropping productivity. Hence, the U-shaped relationship between the DE and FP may be steeper for firms in China's central region.

Firms in the western region, on the other hand, are the least developed (Pan et al., 2022). The intricacy of the DE is thus not as important to them as it is to their counterparts in the eastern and central regions. As a result, they can benefit from implementing DE within the organization at a very low cost throughout the early stages of DE development. Meanwhile, the development of DE has decreased the cost of interregional resource mobility, thereby accelerating the migration of labor, money, and other resources from developed to developing regions (Du and Zhang, 2021). Consequently, firms in the western region, as latecomers, may capitalize on DE development to significantly and rapidly enhance FP by avoiding errors and learning from their peers. Thus, rather than experiencing a digital vacuum, western firms may experience rapid productivity growth by adopting a digitized strategy. When firms in the eastern and central regions complete the transformation and market rivalry intensifies, however, firms in the western region are likely to experience declining productivity.

We present the following hypotheses based on the above argument:

Hypothesis 2a. A moderate U-shaped relationship exists between the DE and FP for firms in the eastern region.

Hypothesis 2b. A steep U-shaped relationship exists between the DE and FP for firms in the Central region.

Hypothesis 2c. An inverted U-shaped relationship exists between the DE and FP for firms in the Western region.

2.3.2. Firm size

Firm size matters significantly in resolving compatibility difficulties. By virtue of their complicated bureaucracy, large firms confront greater compatibility challenges in terms of employees, business processes, and culture (Du and Zhang, 2021). Given similar stages of DE development, large firms find it more difficult than small firms and are, therefore, hesitant to shift from a non-digitized to a digitized strategy. Large firms must plan ahead for a seamless transition. As a result, large firms may endure a slower decline in productivity throughout the DE development process as well as a lengthier period of digital vacuum during the transition. In sum, the U-shaped link between the development of the DE and FP may be moderate for large firms.

Medium firms, on the other hand, may experience fewer compatibility issues. As a result, medium firms are likely to face a shorter period of digital vacuum. They may complete the transition more quickly than large firms, allowing for a longer ascending productivity process. In sum, the U-shaped link between DE and FP may be substantially steeper for medium firms.

In contrast, small firms are the most adaptable (Krishnan et al., 2015) because they can respond swiftly by taking advantage of the DE while avoiding the complicated compatibility issues. Meanwhile, because the complexity of digital technology and infrastructure is not as critical for most small firms, they may introduce a low-cost application of digital technology at the early stage of DE development. Such a digitized strategy will dramatically and rapidly increase small firms' productivity. For example, the growth of e-commerce trading platforms and mobile payment alleviates market segmentation caused by space–time separation while also widening the sales channels available to small firms (Bell et al., 2012; Brynjolfsson and Hitt, 2000). When, as a result, the marginal cost of capacity expansion is minimized, economies of scale occur (Hsieh and Klenow, 2009). For example, following the outbreak of the COVID-19 pandemic, Guangdong Xinbao Electrical Appliances began focusing on the e-commerce model not only by utilizing social media influencers to promote sales via live streaming but also by experimenting with other online channels, such as new retail and new marketing, to reach more consumers. Through its use of e-commerce, Xinbao Electrical Appliances has consistently built brand recognition, reduced market reaction time, and achieved a net interest rate of 15 %. However, as the DE evolves and more firms adopt a digitized strategy, small firms will be forced to compete more vigorously, resulting in a decline in their productivity. The U-shaped relationship between DE and FP in small firms, similar to firms in the western region, may thus become inverted.

We present the following hypotheses based on the above argument:

Hypothesis 3a. A moderate U-shaped relationship exists between the DE and FP for large firms.

Hypothesis 3b. A steep U-shaped relationship exists between the DE and FP for medium firms.

Hypothesis 3c. An inverted U-shaped relationship exists between the DE and FP for small firms.

3. Research design

3.1. Sample and data

To empirically test the proposed U-shaped relationship, we collected a large set of data from multiple sources. Specifically, we chose the firms listed in China's A-share market, including the Shanghai Stock Exchange and Shenzhen Stock Exchange, as our sample. The firm-level information was from the China Stock Market & Accounting Research database and Wind, while the city-level information was from China City Statistical Yearbook. To ensure the validity of the data, we eliminated the following firms from the sample: (a) firms that had suffered consecutive losses (marked as ST or *ST); (b) firms in the finance industry; (c) firms with a serious lack of information; (d) firms with a registered address that did not match the city-level data.

Due to limited data availability on the DE, we restricted the sample period to 2016–2019. To reduce the influence of extreme observations, we winzorized all continuous variables at 1 %. Ultimately, we obtained a total of 10,739 observations.

3.2. Variables

3.2.1. Dependent variable

To measure FP, we used the natural logarithm of total factor productivity (*Tfp*). We employed the Wooldridge method to measure total factor productivity at the firm level and adopted the Levinsohn–Petrin (LP) method and the LP method with Ackerberg–Caves–Frazer correction (LP–ACF) for the robustness test. The LP method takes an intermediate product input as the proxy variable, which ensures that the selection of the proxy variable is flexible according to data availability (Levinsohn and Petrin, 2003). When using the LP method to estimate the total factor productivity, the free variables and proxy variables must be independent of one another, or the collinearity between the estimation coefficients may impair the consistency of the estimation results (Ackerberg et al., 2015). The LP–ACF method remedies this problem. Wooldridge (2009) suggested a one-step estimation technique based on the generalized method of moments. It not only eliminates the potential identification difficulty of the LP method but also yields a robust standard error when considering sequence correlation and heteroscedasticity.

In the specific calculation, according to Giannetti et al. (2015), Guariglia et al. (2011), and Krishnan et al. (2015), the total output (Y) is measured as the main business income of the firm, the labor input (L) is measured as the cash paid to and for employees, the capital input (K) is measured as the net fixed assets, and the intermediate product input (M) is calculated as the "operating cost + sales expense + administrative expense + financial expense − depreciation of fixed assets − depletion of oil and gas assets − depreciation of productive biological assets − cash paid to and for employees."

3.2.2. Independent variable

We used the China "Internet Plus" Digital Index (*Digitaldex*) to measure the development of the DE. The Tencent Research Institute has released the China "Internet Plus" Digital Index since 2016. Since 2019, however, the index has been termed the Digital China Index. The index is compiled based on big data from Tencent, JD.com, DiDi, meituan, Ctrip, Pinduoduo, dianping.com, and other digital platforms, using a wide variety of indicators, such as cloud consumption, number of cloud virtual machines, flow rate of content delivery network, and storage of continuous data protection as well as WeChat and QQ data. Meanwhile, using indicators such as mobile payment, e-commerce, WeChat urban services, and WeChat subscriptions of government administration, the index also depicts the development level of digital finance and digital government in cities. Therefore, we utilized the China "Internet Plus" Digital Index to match the firm data. In doing so, we were able to determine the development stage of the DE from various perspectives, including digital infrastructure, digital finance, and digital government (Du and Zhang, 2021; IMF, 2018).

3.2.3. Control variables

We included a set of firm- and city-level control variables with the potential to influence the dependent variable *Tfp* (Guariglia et al., 2011). Among the firm-level control variables, we measured firm size (*size*) as the natural logarithm of the total assets of a firm, firm age (*age*) as the natural logarithm of the number of years since the firm was established, the proportion of fixed assets in total assets (*pft*) as the ratio of net fixed assets to total assets, the asset–liability ratio (*loar*) as the ratio of total liabilities to total assets, and equity concentration (*contl*) as the proportion of the largest shareholder in all shares. Among the city-level control variables, we measured urban economic development level (*gdp*) as the natural logarithm of the GDP of the city where the firm had registered and urban permanent population (*popu*) as the natural logarithm of the permanent population of the city where the firm had registered.

3.3. Model specification

To investigate the impact of DE on the productivity of Chinese firms, we established the following panel model for empirical research:

$$Tfp_{i,t} = \alpha + \beta_1 Digitaldex_{c,t} + \beta_2 Digitaldex_{c,t}^2 + \gamma E_{i,t} + \delta C_{c,t} + \mu_h + \mu_t + \varepsilon_{i,t}$$

where i denotes individual firms, c denotes cities, and t denotes time in years. $Tfp_{i,t}$ is the productivity of firm i in year t; $Digitaldex_{c,t}$ is the digital index of the city c where the firm was registered in year t; $Digitaldex_{c,t}^2$ is introduced as an exponential square term to determine whether a nonlinear relationship exists between the DE and FP; $E_{i,t}$ and $C_{c,t}$ represent the control variables at the firm and city level, respectively; μ_h is the industry fixed effect of the model; μ_t is the year fixed effect of the model; and $\varepsilon_{i,t}$ is the error term of the model. In addition, we clustered the robust standard errors at the city level to mitigate the estimation result deviation caused by the correlation of firms within the city.

4. Empirical results

4.1. Full-sample regression analysis

Table 2 presents the descriptive statistics and correlations of all variables in the model. None of the correlation coefficients among the control variables and independent variables were high. The results also suggest that multicollinearity was not a concern in the samples. The full-sample regression results of the panel data fixed effect model through the Hausman test are shown in Table 3. Model 1 contains only control variables and acts as the baseline model. In Models 2 and 3, we added the independent variable (*Digitaldex*) and the square of the independent variable (*Digitaldex*^{2}) stepwise to the baseline model. Model 2 analyzes the linear relationship between the development of the DE and FP. The regression coefficient of *Digitaldex* was negative at the significance level of 5 %, indicating that the development of the DE inhibits the productivity growth of Chinese firms to some extent. Model 5 examines the nonlinear relationship between the development of the DE and FP. It shows that the coefficient of *Digitaldex* remained negative at the significance level of 1 %, while the coefficient of *Digitaldex*^{2} was positive at the significance level of 5 %. Among the control variables, the coefficient of *size* was positive at the significance level of 1 %, and the coefficients of *pft* and *gdp* were negative at the significance levels of 1 % and 5 %, respectively, while the coefficients of *age*, *loar*, *contl*, and *popu* were insignificant. The regression results reveal a U-shaped relationship between the development of the DE and FP.

Notably, the value of the turning point of the U-shaped curve can be calculated from the regression results. The turning-point values of the U-shaped curve shown in Models 3, 4, and 5 are 29.7, 27.7, and 28.4, respectively. All three fall within the interval of the independent variable [0.0462, 35.7336], meaning that the relationship between the development of the DE and FP was primarily nonlinear during the sample period (i.e., 2016–2019). Therefore, we selected the nonlinear model containing *Digitaldex*^{2} for empirical analysis. The value of the turning point of the U-shaped curve indicates that when the value of *Digitaldex* was lower than the turning point value of 28.4, the development of the DE inhibited FP. In contrast, when the *Digitaldex* value exceeded 28.4, the development of the DE promoted FP.

Based on the regression results, we used Stata 16.0 to fit the U-shaped curve. In Fig. 3, the solid line indicates the impact of the development of the DE on FP during the sample period, while the dotted line represents a possible future trend in the impact of the development of the DE on FP. The value on the horizontal axis represents the level of DE development. A smaller value indicates low levels of DE development, and a higher value suggests higher levels. The value on the vertical axis is FP. A smaller value implies a lower FP, and a higher value represents a higher FP. Consistent with Hypothesis 1, between 2016 and 2019, the productivity of Chinese firms first declined and then increased with the

Table 2
Descriptive statistics and correlations between study variables.

Variables	Observations	Mean	Std. Dev.	Min	Max	1	2	3	4	5	6	7	8	9
1. Tfp	10,739	12.9845	1.0027	10.9255	15.8319	1.000								
2. Digitaldex	10,739	7.6954	9.3959	0.0462	35.7336	0.088	1.000							
3. size	10,739	22.2661	1.3272	19.9349	26.3050	0.815	0.065	1.000						
4. age	10,739	5.3886	0.3042	4.5539	5.9789	0.135	−0.009	0.168	1.000					
5. pft	10,739	0.1959	0.1507	0.0020	0.6663	−0.080	−0.203	0.089	0.045	1.000				
6. loar	10,739	0.4149	0.1999	0.0610	0.8913	0.510	0.035	0.543	0.170	0.051	1.000			
7. contl	10,739	33.6769	14.4517	8.4468	73.0561	0.180	0.027	0.185	−0.032	0.091	0.060	1.000		
8. gdp	10,739	18.1206	1.1205	15.2074	19.6049	0.075	0.702	0.043	−0.045	−0.253	0.016	0.043	1.000	
9. popu	10,739	6.4366	0.6644	4.5799	8.1242	0.061	0.387	0.072	0.010	−0.130	0.005	0.043	0.676	1.000

Note. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3
Regression results for the full sample.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Digitaldex		−0.0012**	−0.0050***	−0.0054***	−0.0047***
		(−2.0911)	(−2.8082)	(−3.3276)	(−2.8235)
Digitaldex^2			0.0001**	0.0001***	0.0001**
			(2.1958)	(2.7102)	(2.1685)
size	0.4376***	0.4377***		0.4379***	0.4380***
	(18.5742)	(18.5478)		(18.4668)	(18.5720)
age	0.1079	0.1181		0.1140	0.1122
	(0.9052)	(0.9853)		(0.9502)	(0.9482)
pft	−1.1249***	−1.1240***		−1.1250***	−1.1234***
	(−11.0790)	(−11.0896)		(−11.1021)	(−11.0704)
loar	0.0110	0.0118		0.0115	0.0125
	(0.2092)	(0.2227)		(0.2148)	(0.2363)
contl	−0.0004	−0.0004			−0.0004
	(−0.2073)	(−0.2163)			(−0.2171)
gdp	−0.0256***	−0.0256***			−0.02321**
	(−3.0883)	(−2.7287)			(−2.4570)
popu	−0.0568	−0.0323			−0.0144
	(−1.0143)	(−0.5680)			(−0.2570)
Constant	3.6097***	3.3978***	14.2283***	3.5055***	3.2748***
	(4.7031)	(4.4179)	(204.1064)	(5.1603)	(4.2711)
Observation	10,739	10,739	10,739	10,739	10,739
R-squared	0.37	0.37	0.17	0.37	0.37
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes

Note. Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

development of the DE.

4.2. Robustness analysis

4.2.1. Endogeneity test

We applied an instrumental variable estimation method to avoid potential endogeneity bias in the model. Consistent with Du and Zhang (2021), we divided the cities where the sample firms were registered into three categories: municipalities directly under the central government, sub-provincial cities, and non-sub-provincial cities in the same province. The China "Internet Plus" Digital Index of cities in the same category (excluding the city where the sample firm was registered) was used as an instrumental variable. We chose this instrumental variable primarily because Chinese cities within the same category typically exhibit significant similarities in terms of their economic development, population density, and administrative authority. In addition, their DE development levels are strongly correlated.

Table 4 presents the endogeneity test results. Model 1 shows the regression results of the first stage of the two-stage least square (2SLS). The estimated coefficient of the instrumental variable is positive at the 1 % significance level, and the value of the first-stage F-statistic is 529.554, thus exceeding the critical value at a significance level of 1 %. This means that the instrumental variable is effective, and the weak instrumental variable issue does not exist. The results for the second-stage 2SLS for Models 2 and 3 are presented in Table 4, before and after the introduction of the square term of the endogenous variable *Digitaldex*^{2}. The results of Model 3 indicate that the development of the DE first inhibited and then promoted FP during the sample period. Therefore, the findings of the full-sample regression analysis remain valid when considering the potential endogeneity issues in the model.

4.2.2. Robustness test

We also investigated the robustness of our initial empirical results. First, we used the LP method and the LP–ACF method to examine the robustness of the measurement of the dependent variable (*Tfp*). The regression results for Models 1–4 are presented in Table 5.

Second, we replaced the independent variable *Digitaldex* with the Peking University Digital Inclusive Financial Index (*Dfdex*) to examine the robustness of the measurement of the independent variable (*Digitaldex*; Du and Zhang, 2021). This index is jointly prepared by the Institute of Digital Finance Peking University and the Ant Group. It objectively and comprehensively reflects the actual development of digital financial inclusion in China by creatively establishing an index of digital financial inclusion from the perspective of innovative Internet finance. The regression results appear in Models 5 and 6 of Table 5. The results suggest that after replacing the dependent and independent variables, the U-shaped relationship between the development of the DE and FP persisted in China during the sample period. This is consistent with the full-sample regression results.

Third, to examine the robustness of the estimation method, we tightened the fixed effects by including the city fixed effect in the regression model. We clustered the robust standard errors at the firm

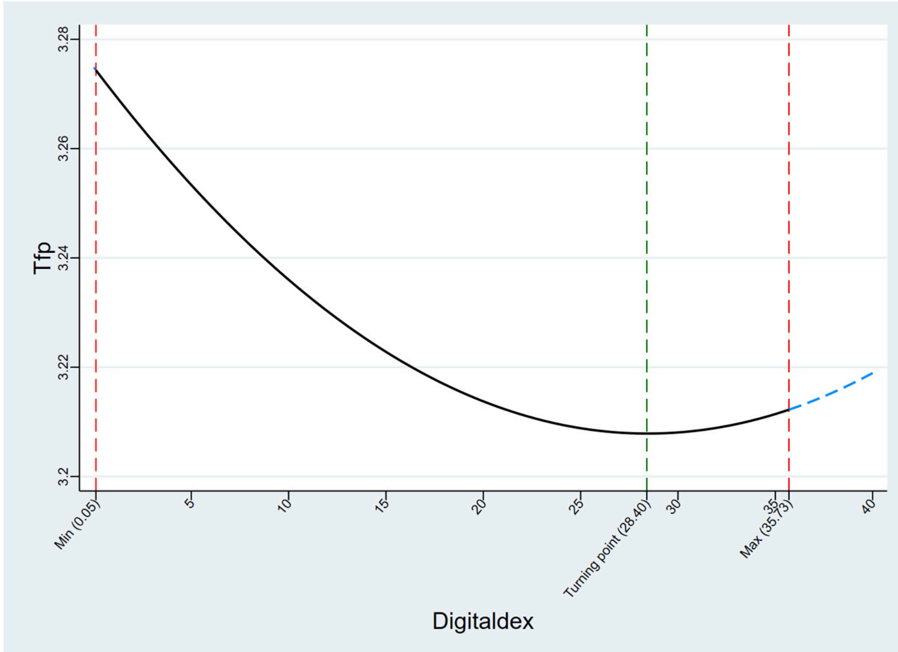


Fig. 3. U-shaped relationship between the development of DE and FP.

Table 4
Regression results for the endogeneity test.

	Model 1	Model 2	Model 3
	Digitaldex	Tfp	Tfp
Digitaldex		−0.0050*	−0.0489**
		(0.0028)	(0.0209)
Digitaldex2			0.0012**
			(0.0006)
Instrumental variable	0.6416***		
	(0.02788)		
size	0.2017***	0.0748***	0.0737***
	(0.5510)	(0.0052)	(0.0053)
age	−1.0943***	−0.0471***	−0.0515***
	(0.1912)	(0.0180)	(0.0181)
pft	−0.9946**	−1.5081***	−1.5280***
	(0.4511)	(0.0449)	(0.0464)
loar	−0.1822	0.4788***	0.4872***
	(0.3495)	(0.0351)	(0.0359)
contl	0.0014	0.0003	0.0004
	(0.0041)	(0.0004)	(0.0004)
gdp	5.2979***	0.0057	0.1060**
	(0.9488)	(0.0187)	(0.0477)
popu	−3.2427***	0.0708	−0.0355**
	(0.1236)	(0.567)	(0.0138)
Constant	−71.5213***	−0.0185	−3.2724***
	(2.1401)	(0.0120)	(0.7518)
First-stage F-statistics	529.554		
Observations	10,739	10,739	10,739
R-squared	0.66	0.44	0.43
Year fixed effect	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes

Note. Robust standard errors in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

level. The regression results for Models 7 and 8 are presented in Table 5.

Finally, we winzorized all continuous variables at 5 % to alleviate the impact of extreme values on the regression results. The results for Models 9 and 10 are presented in Table 5; these suggest that the full-sample regression results remain robust, thus supporting Hypothesis 1.

4.3. Sub-sample regression analysis

We conducted a sub-sample regression analysis on the sample firms by locality and size to comprehensively investigate the impact of DE development on the productivity of Chinese firms based on firm-specific characteristics.

4.3.1. Sub-sample regression analysis by firm locality

We divided the sample into three sub-samples based on firm locality: firms in the eastern region, firms in the central region, and firms in the western region. The eastern region includes Beijing, Shanghai, Tianjin, Liaoning, Hebei, Shandong, Jiangsu, Zhejiang, Fujian, Guangdong, and Hainan; the central region includes Heilongjiang, Jilin, Shanxi, Henan, Anhui, Hubei, Hunan, and Jiangxi; and the western region includes Guangxi, Yunnan, Guizhou, Sichuan, Chongqing, Shaanxi, Gansu, Ningxia, Inner Mongolia, Xinjiang, Qinghai, and Tibet. The results for Models 1, 2, and 3 are presented in Table 6 for the eastern, central, and western regions, respectively.

The regression results in Model 1 show that the coefficient of *Digitaldex* is negative at a significance level of 1 %, while the coefficient of *Digitaldex*^{2} is positive at a significance level of 1 %, indicating a U-shaped relationship between DE development and FP in the eastern region. According to the regression results for Models 2 and 3, however, the development of the DE in the central and western regions has no significant impact on FP.

Based on the regression results for firms in the eastern, central, and western regions, we fitted the curves in detail in Fig. 4a, b, and c, respectively. Fig. 4a depicts the eastern region. It shows a moderate U-shaped curve, in which the turning point value for *Digitaldex* is 25.9. The shape and the turning point support Hypothesis 2a. Meanwhile, DE development and FP exhibit a steep U-shaped relationship for firms in the central region. The turning point value for *Digitaldex* is 10.9, and the maximum value is 9.3968, suggesting that firms in the central region remain on the left side of the steep U-shaped curve and have not completed the transition. Although the regression result does not support Hypothesis 2b, the curve depicted in Fig. 4b partly supports our argument. The regression results also fail to support Hypothesis 2c for firms in the western region. Fig. 4c shows that for these firms, DE development and FP do not exhibit an inverted U-shaped relationship.

Table 5
Regression results for the robustness test.

	Model 1 (LP)	Model 2 (LP)	Model 3 (LP–ACF)	Model 4 (LP–ACF)	Model 5 (Dfdex)	Model 6 (Dfdex)	Model 7 (City-fixed effect)	Model 8 (City-fixed effect)	Model 9 (5 % winsorization)	Model 10 (5 % winsorization)
Digitaldex	−0.0012**	−0.0047***	−0.0009*	−0.0048***			−0.0012*	−0.0049**	−0.0012*	−0.0048**
	(−2.0884)	(−2.8313)	(−1.9262)	(−2.6431)			(−1.8434)	(−2.1754)	(−1.9052)	(−2.3074)
Digitaldex^2		0.0001**		0.0001**				0.0001*		0.0001*
		(2.1787)		(2.1267)				(1.7378)		(1.7260)
Dfdex					−0.0005***	−0.0061***				
					(−2.9485)	(−3.6453)				
Dfdex^2						0.00001***				
						(3.4328)				
size	0.4301***	0.4304***	0.0614**	0.0617**	0.4383***	0.4390***	0.4379***	0.4382***	0.4289***	0.4291***
	(18.3116)	(18.3360)	(2.1080)	(2.1234)	(18.7943)	(18.7823)	(16.7726)	(16.7805)	(20.3188)	(20.3221)
age	0.1125	0.1065	−0.1744	−0.1809	0.1240	0.1451	0.1168	0.1100	0.1991*	0.1948*
	(0.9367)	(0.8992)	(−1.1635)	(−1.2249)	(1.0212)	(1.1877)	(0.8175)	(0.7739)	(1.7616)	(1.7212)
pft	−1.1340***	−1.1334***	−1.1697***	−1.1690***	−1.1205***	−1.1195***	−1.1212***	−1.1207***	−1.0618***	−1.0622***
	(−11.1929)	(−11.1737)	(−10.6540)	(−10.6490)	(−11.0155)	(−11.0153)	(−11.0924)	(−11.0787)	(−10.9104)	(−10.8937)
loar	0.0104	0.0112	−0.0789	−0.0781	0.0109	0.0132	0.0142	0.0150	0.0410	0.0414
	(0.1981)	(0.2119)	(−1.2994)	(−1.2919)	(0.2061)	(0.2501)	(0.2186)	(0.2313)	(0.7808)	(0.7856)
contl	−0.0004	−0.0004	−0.0005	−0.0005	−0.0003	−0.0004	−0.0004	−0.0004	−0.0008	−0.0008
	(−0.2235)	(−0.2242)	(−0.2603)	(−0.2608)	(−0.1980)	(−0.2320)	(−0.2412)	(−0.2446)	(−0.4479)	(−0.4597)
gdp	−0.0254***	−0.0230**	−0.0179*	−0.0153	−0.0195**	−0.0211***	−0.0287***	−0.0266***	−0.0197*	−0.0174*
	(−2.7165)	(−2.4444)	(−1.8227)	(−1.5750)	(−2.4278)	(−2.6269)	(−3.1650)	(−2.9273)	(−1.9444)	(−1.7432)
popu	−0.0323	−0.0143	−0.0250	−0.0055	−0.0505	−0.0155	−0.0771	−0.0508	0.0059	0.0151
	(−0.5702)	(−0.2576)	(−0.4970)	(−0.1119)	(−0.9434)	(−0.3050)	(−0.7830)	(−0.5098)	(0.0995)	(0.2611)
Constant	3.3298***	3.2067***	0.4000	0.2661	4.2638***	3.8818***	3.6896***	4.3023***	3.5926***	2.7259***
	(4.3120)	(4.1639)	(0.3384)	(0.2275)	(5.2050)	(5.0613)	(3.2465)	(3.5884)	(4.5365)	(3.7219)
Observations	10,739	10,739	10,739	10,739	10,739	10,739	10,739	10,739	10,739	10,739
R-squared	0.36	0.36	0.10	0.11	0.37	0.37	0.37	0.37	0.36	0.36
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect							YES	YES		

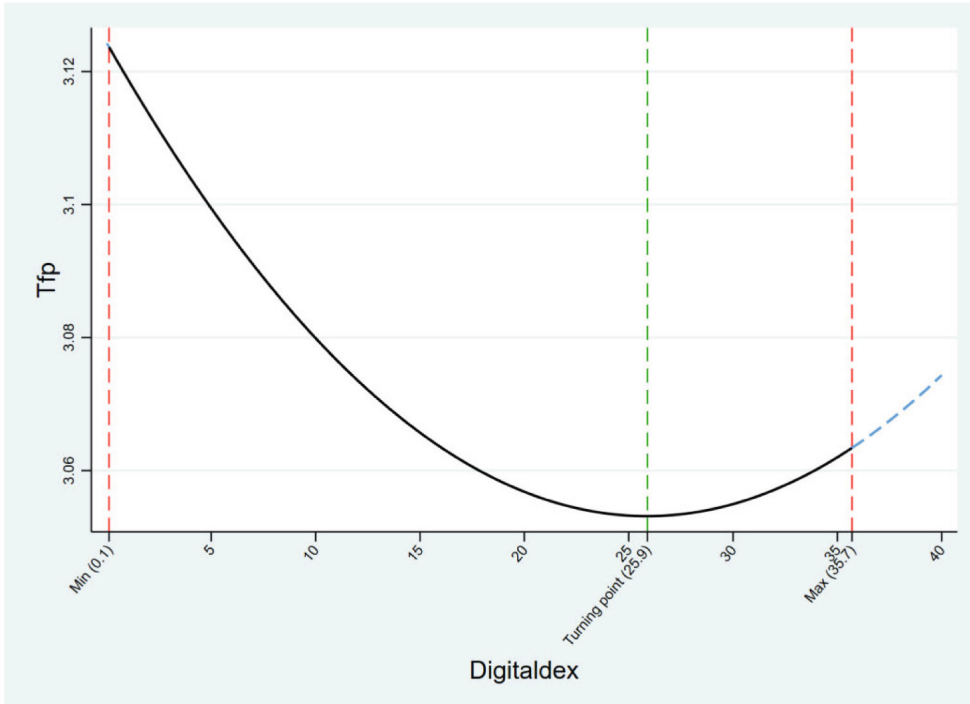
Note. Robust t-statistics in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

Table 6
Regression results for the sub-sample by firm locality and firm size.

	Model 1 (Eastern)	Model 2 (Central)	Model 3 (Western)	Model 4 (Large)	Model 5 (Medium)	Model 6 (Small)
Digitaldex	−0.0055***	−0.0157	0.0071	−0.0077**	−0.0009	0.0015
	(−3.3803)	(−1.2900)	(0.4891)	(−2.5661)	(−0.2028)	(0.3816)
Digitaldex^2	0.0001***	0.0007	0.0002	0.0001*	0.00003	−0.0001
	(2.7355)	(0.6956)	(0.2623)	(1.8581)	(0.5167)	(−0.9331)
size	0.4303***	0.4388***	0.4712***	0.3826***	0.4956***	0.2996***
	(13.3094)	(13.0114)	(9.0596)	(11.8088)	(10.6582)	(3.8653)
age	0.1552	0.0185	0.0962	0.3187*	0.5133	−0.6299
	(1.4576)	(0.0332)	(0.2079)	(1.7088)	(1.3822)	(−1.5768)
pft	−1.1647***	−1.0933***	−1.0239***	−1.1314***	−1.1392***	−1.2546***
	(−9.8188)	(−7.7205)	(−3.1794)	(−7.6381)	(−8.5627)	(−6.2890)
loar	0.0079	0.1295	−0.0534	−0.2331**	−0.0310	0.2623*
	(0.1222)	(1.0902)	(−0.4071)	(−2.3090)	(−0.2377)	(1.8232)
contl	0.0008	−0.0037**	−0.0001	−0.0026**	0.0016	−0.0091**
	(0.3206)	(−2.2224)	(−0.0446)	(−2.3021)	(0.4337)	(−2.1723)
gdp	−0.0206*	−0.0177	−0.0396	−0.0244	−0.0354**	0.0060
	(−1.8620)	(−1.1137)	(−1.1877)	(−1.5815)	(−2.3479)	(0.2376)
popu	0.0212	0.1820**	−0.6654***	−0.0576	−0.2393	0.0473
	(0.3217)	(2.5721)	(−2.7166)	(−0.9321)	(−0.8962)	(0.5297)
Constant	3.1242***	2.8378	6.9384*	4.1037***	1.2465	9.0039***
	(3.3121)	(1.0968)	(1.9875)	(3.0552)	(0.3805)	(3.9763)
Observations	7645	1699	1395	5717	3160	1862
R-squared	0.35	0.50	0.32	0.28	0.24	0.26
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes

Note. Robust t-statistics in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

a



b

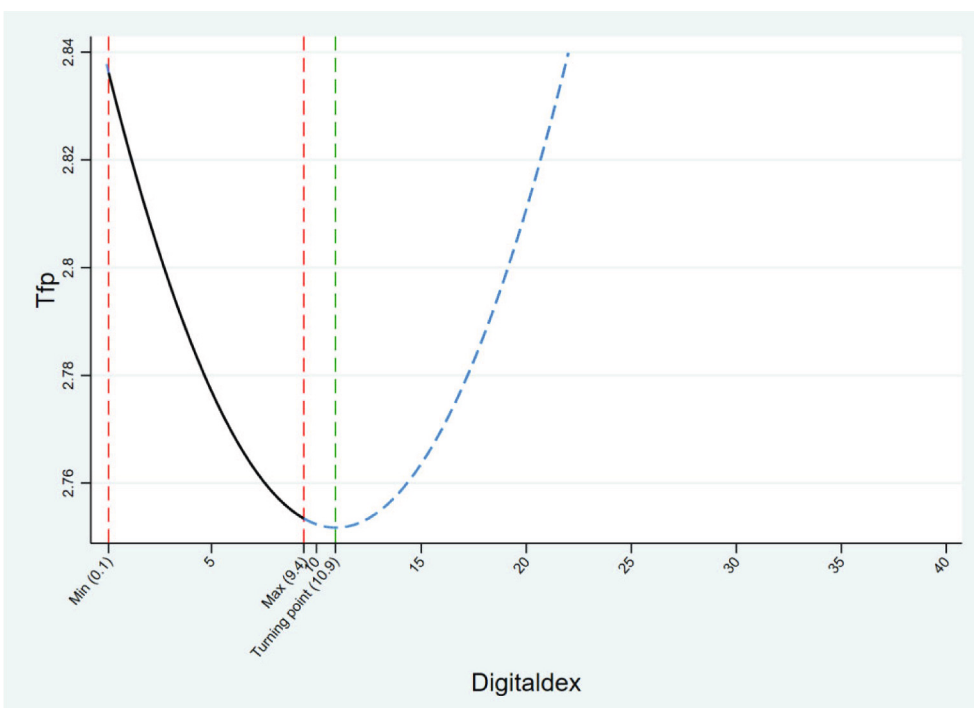


Fig. 4. a. Relationship between DE and FP in the eastern region of China.
b. Relationship between DE and FP in the central region of China.
c. Relationship between DE and FP in the western region of China.

However, an upward trend is evident, indicating that firms in the western region can boost their productivity at the early stage of the DE via their latecomer advantage. Notably, Fig. 4c indicates that firms in the western region have not yet reached the peak of FP, suggesting that they will continue to benefit from DE development.

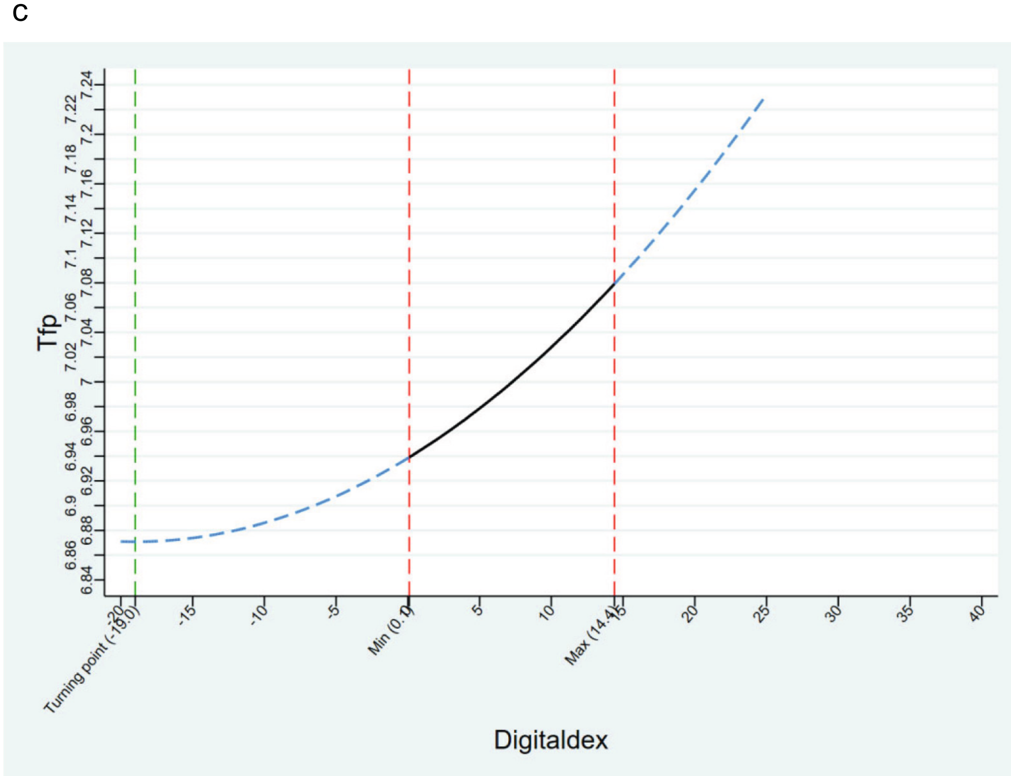


Fig. 4. (*continued*).

4.3.2. Sub-sample regression analysis by firm size

We divided the firms into three sub-samples based on size: large, medium, and small; the regression results for Models 4, 5, and 6 in Table 6 pertain to the regression results for large, medium, and small firms, respectively.

The results in Model 4 reveal that the coefficient of *Digitaldex* is negative at a significance level of 5 %, while the coefficient of *Digitaldex*^{2} is positive at a significance level of 10 %. This indicates a U-shaped relationship between the development of the DE and FP for large firms. The results in Models 5 and 6 show that the development of the DE had an insignificant impact on the productivity of medium-sized and small firms, respectively.

Based on the regression results for large, medium, and small firms, we fitted the curves in detail in Fig. 5a, b, and c, respectively. Fig. 5a depicts a U-shaped curve in which the turning point value for *Digitaldex* is 31.3. This indicates that large firms require a lengthy period of preparation to complete the digital transition. Therefore, the results support Hypothesis 3a. Fig. 5b depicts a U-shaped curve with a turning point value of 9.4, indicating that medium-sized firms take a relatively shorter period to prepare to alter their digitization strategies. Although the regression result is insignificant, Fig. 5b thus partly supports Hypothesis 3b. Fig. 5c shows an inverted U-shaped relationship with a turning point value of 9.2. This suggests that small firms enjoy a very short-term increase in productivity but encounter a subsequent decline. Although this regression result is again insignificant, Fig. 5c partly supports Hypothesis 3c.

5. Discussion and conclusions

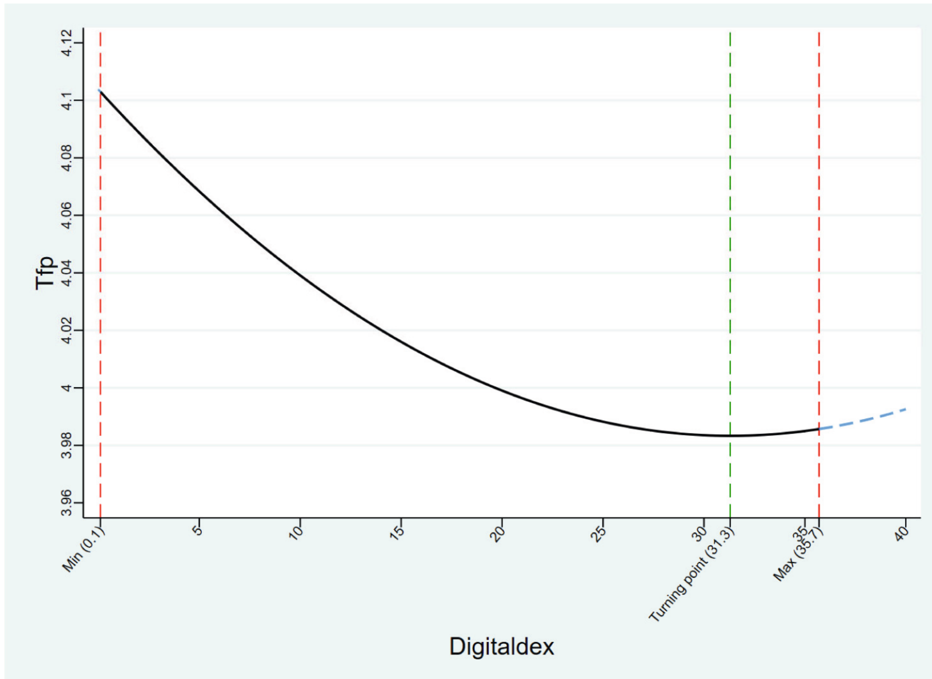
5.1. Theoretical implications

Our analysis contributes to studies on both the general DE–FP relationship and the idiosyncratic effects of firm size and locality on the DE–FP relationship for Chinese firms. First, our study is among the first to conceptualize and investigate the productivity consequences of DE development in Chinese firms. We analyze 10,739 firm-level observations from 2016 to 2019 and find that, for Chinese firms in general, DE development and FP have a nonlinear U-shaped relationship. Initially, DE development is associated with a decrease in FP. However, in later stages, DE development is associated with an increase in FP. In other words, Chinese firms are likely to experience a decline in productivity if they opt for a digitized strategy early in the process of DE development. However, they will reap the benefits later.

In the case of ICT investment, our results confirm the hypothesis of a U-shaped relationship; linear (either upward or downward) curves are merely sub-stages of the main U-curve hypothesis. It is especially fascinating that our findings, which are based on data from Chinese firms, may also explain the contradictory results of earlier studies on ICT investment and the productivity paradox. Specifically, we propose that researchers take into account the DE development stages and firms' strategic choices. Indeed, these factors account for the curvilinear nature of the relationship between the DE and FP relationship. Thus, our findings contribute to a more nuanced understanding of the productivity paradox, indicating that arguments derived from earlier investigations of firms in developed countries may also be relevant to Chinese firms.

Second, our findings have substantial implications for research into how firm idiosyncrasies shape the relationship between the DE and FP in China. We build a conceptual model by illustrating how DE development and two distinct firm-specific factors (firm size and locality) impact the productivity outcomes of Chinese firms. While previous studies have revealed the DE's broad influence on Chinese firms (e.g., Pan et al., 2022; Sun et al., 2017), there has been little research on which types of firms are more affected.

Our findings also emphasize the importance of the firm-specific context in the complex and constantly shifting relationship between the DE and FP in heterogeneous firms. While firms do not benefit equally from DE development, our analysis advances research in this area by uncovering the firm-specific contexts underpinning DE development in a



b

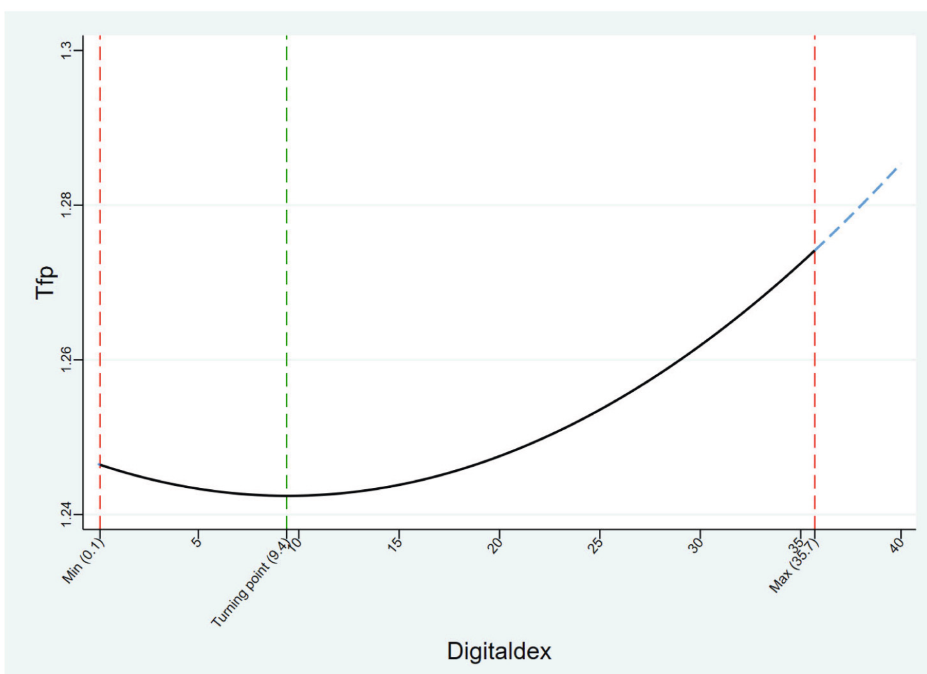


Fig. 5. a. U-shaped relationship between DE and FP of large firms in China.
b. U-shaped relationship between DE and FP of medium firms in China.
c. The U-shaped relationship between DE and FP of small firms in China.

China. Thus, we provide more thorough knowledge on the impact of the firm-specific context on firms' choice of digitized or non-digitized strategies to improve productivity. We contribute to the literature on the DE–FP relationship and the productivity paradox by demonstrating that the relationship is shaped by different digital vacuums arising from compatibility-related difficulties and technological complexities. Our findings suggest that the benefits of DE development are not consistent across firms. Our study thus answers the call for a more nuanced explanation of the productivity paradox, which states that the existence of the productivity paradox depends on firm-specific contexts.

C

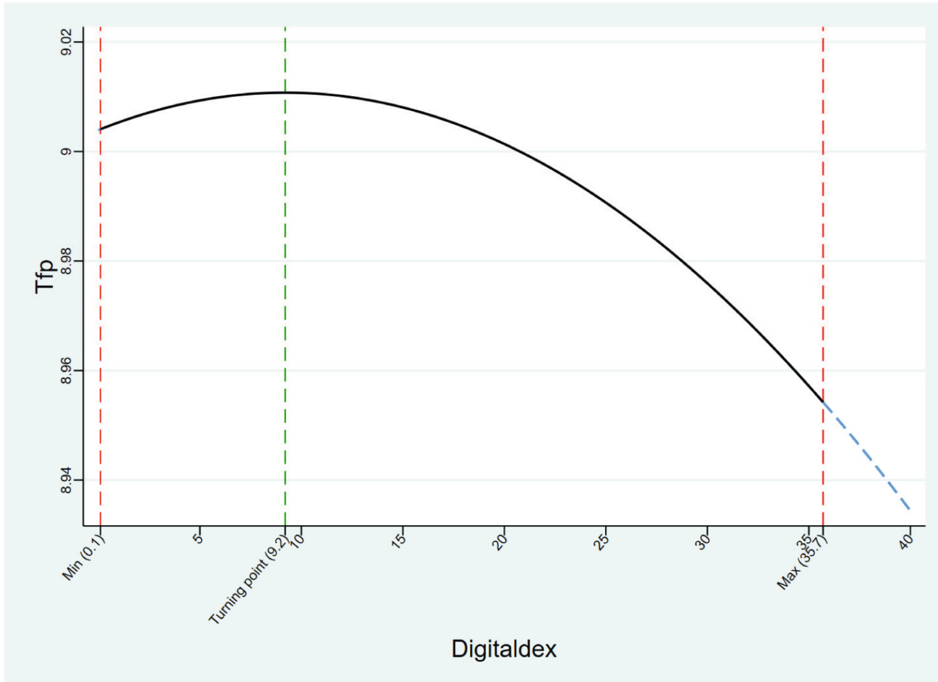


Fig. 5. (*continued*).

Third, we propose an alternative interpretation of the strategic choice to digitize at the various stages of the DE development process. We explain how the cost structures of non-digitized and digitized strategies differ at the early and advanced stages of DE development. The study finds that firms often opt for a strategy based on its relative cost advantages. When DE development is in its infancy, firms will choose a non-digitized strategy because of the high fixed costs and rising marginal costs required to internalize the advantages of a DE. In contrast, once DE development has advanced, firms are likely to adopt a digitized strategy due to the low fixed costs and diminishing marginal costs associated with its implementation. Firms suffer from a digital vacuum during the transition from a non-digitized to a digitized strategy when compatibility concerns arise and productivity plummets. Therefore, we propose a novel theoretical framework that adds value to existing research in respect of strategic digitization; the literature currently focuses on the technical and innovation aspects of the relationship between DE and FP.

5.1.1. *Managerial implications*

Our results have significant managerial implications for Chinese firms and those in emerging economies. First, our research offers essential insights to address questions confronting Chinese firms: Is a digital strategy indeed the best choice? If so, how can firms make the transition from a non-digitized to a digitized strategy? Our findings suggest that a non-digitized strategy is better for firms at the early stage of DE development, while a digitized strategy may be better for firms at the advanced stage of DE. However, these firms are more likely to endure a digital vacuum during the transition. Chinese firms must be patient and confident and remain aware of this potential vacuum to reap the full advantages of a digitized strategy. Although there are potential advantages to adopting such a strategy, firms must address compatibility concerns as efficiently as possible in this period. Firms in emerging economies should thus attempt to learn from successfully digitized firms. In doing so, they may be able to shorten the duration of the digital vacuum.

Second, our findings reveal that firms in emerging economies should recognize how diverse firm-specific contexts influence the productivity outcomes of their digitization initiatives. Our findings on these outcomes for heterogeneous firms in China should assist in better understanding the critical role that a more flexible organizational structure and latecomer advantage play in overcoming disadvantages and facilitating successful digitization efforts. Examples include small and medium firms and those in the central and western regions, that, due to their flexibility and latecomer advantage, are more likely to benefit from digitization efforts than are large firms and those from the eastern region; the latter should prioritize organizational management and capitalize fully on their first-mover advantage.

5.2. *Policy implications*

Our findings also have substantial policy implications. First, understanding the productivity implications of digitization strategies can help Chinese authorities to promote the DE more effectively. The findings demonstrate the explicit heterogeneity in productivity among firms of varying sizes. Specifically, small and medium firms reap the benefits of DE development more quickly than do large firms. Thus, it is critical for Chinese authorities to explore multiple policy alternatives for sustaining DE development and thereby lower the cost of internalizing the advantage of DE development for Chinese firms.

Second, our findings indicate that there is significant regional heterogeneity in the process of DE development in China. We argue that preferential policies are important to accelerate the construction of digital infrastructure in the under-developed central and western regions and to support the coordinated and high-quality development of regional DE.

5.3. *Limitations and future research*

Future research on the DE, particularly in the context of emerging economies, should work to address the limitations of our study. First, our focus on a sample of Chinese firms may limit the generalizability of our findings to other emerging economies. Because technological environments and marketplaces differ significantly across countries, Chinese firms may not adequately reflect their counterparts in other emerging economies. Our empirical results fail to consider this heterogeneity and should thus be interpreted cautiously. Future studies should thus include data on firms from other emerging and developed economies to enhance the validity of the findings.

Second, data limitations led us to focus solely on two types of firm-specific factors: size and locality. However, additional factors may explain firm contexts and hence influence the DE–FP relationship (Wamba et al., 2017). Consequently, future research should consider a model that includes the impact on the DE–FP relationship of various firm-specific factors, such as digital capabilities, financing constraints, and ownership diversity. Finally, due to data availability issues, we only cover data from 2016 to 2019, which may limit the robustness of our findings to some extent. Future research can overcome this problem with a more long-term study.

CRediT authorship contribution statement

Zhe Sun: Conceptualization, Methodology, Data Curation, Formal analysis, Writing – Original Draft

Liang Zhao: Conceptualization, Supervision, Data Curation, Writing – Original Draft,

Review & Editing

Puneet Kaur: Conceptualization, Research Method & Validation, Review & Editing

Nazrul Islam: Supervision, Conceptualization, Research Method & Validation, Review & Editing

Amandeep Dhir: Supervision, Conceptualization, Research Method & Validation, Review & Editing

Data availability

The authors are unable or have chosen not to specify which data has been used.

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